Mobile Phone-Based Surveillance for Foot and Mouth Disease in Cattle

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Dedication

I dedicate this research project to my late Father Mr. Ojok Alfred who laid my foundation and believed in my education. To my mother Mrs. Ayat Madelena Ojok, who always took pride in my education and was ready to support at any cost. My beloved Wife Mrs. Anena Harriet, and my children Ms. Apiyo Mercy Sunday and Mr.Oketayot Austin for their encouragement throughout the research process. Not forgetting Uncle Onen Charles who shouldered all the financial responsibility of seeing me through A-Level until Undergraduate program.

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Abbreviations and Acronym

AI	Artificial Intelligence
API	Application Programming Interface
CDL	Central Diagnostic Laboratory
CNN	Convolutional Neural Network
COVID-19	Coronavirus Disease 2019
COVAB	College of Veterinary Medicine Animal Resource and Biosecurity
DAPH	Department of Animal Production and Health
DEFRA	Department for Environment, Food and Rural Affairs
DVO	District Veterinary Officer
FMD	Foot and Mouth Disease
GDP	Gross Domestic Product
GIS	Geographic Information System
GUREC	Gulu University Research Ethics Committee
ICT	Information and Communication Technology
IDE	Integrated Development Environment

IDSAS	Infectious Disease Surveillance and Analysis System
IoT	Internet of Things
ISID	International Society for Infectious Disease
MAAIF	Ministry of Agriculture, Animal Industries and Fisheries
ML	Machine Learning
NAADS	National Agricultural Advisory Services
NADDEC	National Animal Disease Diagnostic and Epidemiology Center
NGOs	Non-Governmental Organizations
NMRCD	Naval Medical Research Center Detachment
PLE	Primary Leaving Examination
RAD	Rapid Application Development
REC	Research Ethics Committee
RSS	Rich Site Summary / Really Simple Syndication
SACIDS	Southern African Centre for Infectious Disease Surveillance
SDK	Software Development Kit
SMS	Short Message Service

SPSS	Statistical Package for the Social Sciences
SVM	Support Vector Machine
TFLite	TensorFlow Lite
TV	Television
UACE	Uganda Advanced Certificate of Education
UCE	Uganda Certificate of Education
UI	User Interface
UNCST	Uganda National Council for Science and Technology
XML	Extensible Markup Language

Abstract

Foot and Mouth Disease (FMD) is a highly contagious viral infection that threatens livestock production and trade, causing severe economic losses in Uganda and beyond. Its surveillance is essential for rapid detection and control. This study investigated the feasibility of a mobile phone-based surveillance system for FMD in cattle populations in Koch Ongako Sub-County, Omoro District. The research employed a mixed-methods design**, c**ombining both quantitative and qualitative approaches in which data were collected from 46 participants (cattle keepers, traders, and local leaders) through structured questionnaires and analyzed using quantitative descriptive statistics and qualitative thematic analysis. A prototype mobile application was developed based on Rapid Application Development (RAD) methodology, incorporating machine learning (TensorFlow Lite) for image-based diagnosis of FMD symptoms. Findings revealed that while 82.6% of stakeholders owned smartphones and 86% expressed willingness to adopt the technology, challenges like low digital literacy constrain effective adoption. The prototype demonstrated strong performance, achieving 91% diagnostic accuracy and an average response time of 2.3 seconds per image. In addition, the system attained a precision of 0.89, a recall of 0.92, and an F1-score of 0.90, indicating balanced and reliable diagnostic performance. Stakeholders valued its usability, offline functionality, and potential to enhance early detection. Compared to existing platforms such as AfyaData, Google Trends, and ProMED-mail, this prototype uniquely integrates community participation with automated AI-driven diagnosis**,** making it highly relevant for rural livestock systems. The research contributes to veterinary epidemiology by demonstrating how mobile technologies can bridge surveillance gaps in resource-limited contexts. Conclusively, mobile-based AI applications strengthens FMD surveillance and empowering farmers

CHAPTER ONE: INTRODUCTION

Foot and Mouth Disease (FMD) represents one of the most highly transmissible viral infections affecting cloven-hoofed animals, including cattle, goats, swine, sheep, and wildlife species such as buffalos. The FMD virus induces characteristic vesicular lesions on the oral cavity, pedal tissues, and mammary glands of susceptible animals, consequently inflicting substantial economic losses to national livestock industries (Guessoum et al., 2024). The implementation of robust surveillance methodologies is therefore critical for mitigating the associated economic impacts.

The overall aim of this study was to design, develop, and evaluate a mobile-based surveillance prototype that leverages artificial intelligence for the detection and reporting of Foot and Mouth Disease (FMD) among cattle in Koch Ongako Sub-County, Omoro District, Uganda.

This research was undertaken in Koch Ongako Sub-County, a predominantly rural area where livestock rearing is becoming a major source of livelihood. The choice of study site was informed by increased livestock farming in the area, importation of many cattle from Lango regions, and the sub county being close to Nwoya district which recently had FMD outbreaks and the challenges faced by local farmers in accessing veterinary services. By introducing a mobile-based prototype into this context, the study sought to assess the readiness of farmers and traders to adopt such technology, evaluate its diagnostic performance, and explore its potential for integration into Uganda’s animal health surveillance systems.

1.1 Background

The historical epidemiology of Foot and Mouth Disease (FMD) traces back to 1514, when Italian monk Hieronymus Fracastorius documented the first recorded observation of characteristic clinical signs in cattle in Venice. His documentation noted distinctive pathological manifestations including oral and pedal vesicular lesions accompanied by inflammation (Jamal and Belsham, 2013). The disease's geographical progression was subsequently documented across Europe, with initial cases reported in Germany (1754) and Great Britain (1839), followed by transcontinental spread to the United States (1870) and South America (1871). While early epidemiological records in Asia and Africa remain limited, South Africa documented its first official case in 1892, and India reported widespread disease occurrence as early as 1864 (Pattnaik et al., 2012).

Uganda had its first documented case of FMD in 1953 (Dr. Chris Rutebarika, 2012). The contemporary global epidemiological data indicates FMD circulation in approximately 77% of livestock populations across Africa, the Middle East, Asia, and portions of South America. FMD-free nations maintaining non-vaccination policies face persistent risk of disease incursion. The economic burden is particularly pronounced in Africa and Eurasia, accounting for 50% and 30% of global costs respectively.

In Uganda, epidemiological surveillance by the National Animal Disease Diagnostic and Epidemiology Center (NADDEC) documented FMD outbreaks across nine districts in early 2015 (Situation, 2015). Moses et al. (2015) reported outbreaks in multiple districts including Kiruhura, Kween, Nwoya, Isingiro, Ntungamo, Rakai, and Wakiso during 2012-2013. Historical data indicates an escalation in outbreak frequency, from 15 annual cases (1996-1999) to 23-28 cases (2000-2007). The peak incidence occurred between January 2013 and December 2014, with 41 outbreaks documented across 33 districts (Natukunda et al, 2015).

The economic implications of FMD manifest through multiple pathways: restricted international market access, decreased milk production affecting both human and calf nutrition, reduced livestock productivity, and elevated juvenile mortality rates. Secondary impacts include diminished animal traction capacity affecting agricultural operations and reproductive losses through abortions, which impose substantial costs through extended nonproductive periods or necessitate culling.

Current surveillance challenges reflect disparate national capacities and requirements. Developed nations with export-dependent livestock sectors maintain sophisticated surveillance systems to safeguard trade interests. Conversely, less developed countries with porous borders and frequent disease incursions face significant constraints in implementing comprehensive surveillance infrastructure, focusing instead on impact mitigation strategies (OIE, 2018).

1.1.1 Surveillance Importance

Disease surveillance systems serve as critical epidemiological tools for early pathogen detection, a fundamental component in preventing disease dissemination and minimizing economic impact. These surveillance frameworks enable veterinary epidemiologists to implement timely interventions before disease progression reaches unmanageable levels. Through systematic monitoring protocols, surveillance systems facilitate the quantification of disease occurrence and prevalence rates, enabling comprehensive pathogen characterization and informing evidence-based control and prevention strategies.

The multifaceted benefits of robust surveillance systems extend to several critical areas of veterinary epidemiology:

Risk Assessment and Spatial Epidemiology: Identification of high-transmission risk zones, Mapping of disease spread patterns and Analysis of geographical and temporal distribution

Program Evaluation: Quantitative assessment of control intervention efficacy, Monitoring of prevention strategy outcomes and Cost-benefit analysis of implemented measures

Epidemiological Trend Analysis*:* Documentation of disease progression patterns, Identification of emerging pathogen variants and Assessment of population-level health indicators

These surveillance frameworks provide essential data for evidence-based decision-making in veterinary public health policy and intervention strategy development. The integration of modern technological tools, particularly mobile-based platforms, has enhanced the capacity for real-time data collection and analysis, facilitating more rapid response to disease outbreaks.

The implementation of comprehensive surveillance systems represents a cornerstone of effective veterinary epidemiology, enabling proactive rather than reactive disease management approaches. This systematic monitoring framework supports both immediate intervention needs and long-term epidemiological research objectives.

1.1.2 Agricultural Mobile Technology Overview

Recent technological advances in ICT have created unprecedented opportunities for agricultural optimization, particularly in crop production and livestock management through enhanced knowledge dissemination networks (Saikanth et al., 2023). The integration of mobile technologies into agricultural systems has demonstrated multiple operational benefits such as:

Information Access and Knowledge Transfer: Enhanced dissemination of technical agricultural data, Real-time access to scientific insights and Facilitation of evidence-based decision-making protocols

***Resource Optimization**:* Improved operational efficiency through data-driven decision support, Enhanced resource allocation methodologies and Implementation of precision agriculture techniques

Market Integration: Disintermediation of agricultural value chains, direct producer-consumer interface establishment and Enhanced market transparency and price discovery mechanisms

Environmental Risk Mitigation: Real-time meteorological data integration, Climate-smart agriculture implementation and Weather-related risk assessment protocols

Financial Management Systems: Digital transaction tracking mechanisms, Automated record-keeping protocols including Enhanced financial planning capabilities

Contemporary technological advancement has facilitated the development of specialized mobile applications for agricultural optimization. Notable implementations include:

i) **AgriApp**: An Android mobile application developed by AgriApp Technologies Pvt Ltd in India. The App is an information portal on crop production and protection, smart farming, acts as online market place which bring together farmers and input retailers to a common digital platform.
ii) **FarmGo**: A Mobile app available on iOS and Android phones and is supporting farmers in Thailand and India to get real time weather forecasts and updates thus allowing them to optimize their farming activities.
iii) **VetWiz:** This is freely available mobile app that allow health practitioners and livestock keepers to carry out disease diagnosis and treatment of animal disease.
iv) **AgriSync:** A tool that connect farmers to advisors from different companies through video calls to receive support in real-time.

The above discussed technological integration represents a significant advancement in agricultural management systems, facilitating enhanced operational efficiency and decision-making capabilities across the agricultural value chain.

1.1.3 Research Context

Given the widespread adoption of mobile technologies and internet connectivity across remote agricultural regions, including rural farming communities in Uganda, mobile platforms present significant opportunities for enhanced disease surveillance implementation. Mobile technology has fundamentally transformed the efficiency of epidemiological data transmission and epidemic intelligence gathering. The pervasive availability and cost-effectiveness of portable smart devices, complemented by their extensive application ecosystem through which animal health data can be acquired and disseminated, establishes mobile technology as an optimal framework for animal disease surveillance systems.

1.1.4 Sources of Problems

According to Knight-Jones and Rushton (2013), Foot and Mouth Disease (FMD) exhibits relatively low mortality rates; however, its global impact is substantial due to the extensive number of animals susceptible to simultaneous infection. The economic implications can be categorized into direct and indirect losses. Direct losses manifest through decreased livestock productivity and alterations in herd demographics, while indirect losses emerge from disease control expenditures, restricted international market access, and limited implementation of enhanced production methodologies.

Specific economic impacts include:

i. Reduced milk production, affecting both human consumption and calf nutrition, accounting for approximately 33% of losses in widespread outbreak scenarios

ii. Diminished livestock growth rates and elevated juvenile mortality (2-5% mortality rate)
iii. Decreased animal traction capacity, disrupting agricultural operations
iv. Reproductive losses through abortions, imposing substantial costs through extended nonproductive periods or necessitating premature culling

The technical precision and academic structure better reflect the epidemiological significance of FMD's economic impact while maintaining the core information from Knight-Jones and Rushton's (2013) analysis.

1.2 Statement of the Problem

As per Wolff et al. (2019), Uganda is a low-income country in East Africa with significant potential for developing its livestock sector. The livestock sector contributed 1.7% to the national GDP in 2009, which is now estimated to be 3.2% of the total GDP, surpassing contributions from both cash crops and fishing (Behnke and Nakirya, 2012). However, Uganda has a high prevalence of FMD, with 41 outbreak cases recorded between 2013 and 2014 across 33 districts (Natukunda et al., 2015). Analysis of FMD outbreaks during 2001-2010 revealed the highest incidence in the Central Region (34%), followed by Eastern (19%), Southwestern (17%), Northern (13%), Western (13%), Northeastern (3%), and Northwestern (1%) regions (G. F. D. Situation, 2012).

Multiple stakeholders, including (Ministry of Agriculture, Animal Industries and Fisheries) MAAIF, (National Agricultural Advisory Services) NAADS, CARITAS, World Vision, and others, have attempted to deliver technical support and advisory services through extension workers to control FMD transmission in cattle throughout the country, albeit with limited success. Current surveillance systems such as AfyaData, Google Trends, and ProMed-Mail have been implemented but cannot fully address FMD surveillance requirements due to delayed data feedback provision, unreliable search functionality, and excessive dependence on organizers and human moderators.

Moreover, these systems were not specifically designed for FMD surveillance. Therefore, there is a critical need to supplement existing stakeholder efforts and surveillance systems by developing a mobile phone application for FMD surveillance, which provide an instant notification given the widespread mobile phone adoption in these communities.

1.3 Main Objective

The main objective of this study was to design and develop a mobile-based surveillance system for the detection of Foot and Mouth Disease (FMD) in cattle.

1.3.1 Specific Objectives

i) To review existing state-of-the-art surveillance systems for Foot and Mouth Disease (FMD) in cattle to identify their capabilities and operational gaps.
ii) To develop a machine learning model for detecting FMD symptomatology in cattle based on the capabilities and gaps identified in objective (i).
iii) To evaluate the proposed system's performance through stakeholder engagement and validation protocols.

1.4 Research Questions

This research addresses critical gaps in FMD surveillance methodologies while exploring innovative technological solutions for enhanced disease monitoring and detection. The following research questions guide the investigation of mobile technology applications in FMD surveillance:

i) What are the operational and technical gaps in current surveillance systems for Foot and Mouth Disease (FMD)?

ii) How can a machine learning-based surveillance system be developed to address the identified gaps in FMD monitoring?

iii) What validation protocols and performance metrics can be employed to evaluate the effectiveness of the proposed surveillance system?

1.5 Research Scope

This research study was conducted in Koch Ongako Sub-county, Omoro district, Uganda. Koch Ongako Sub-county is experiencing a significant transition from crop cultivation to livestock agriculture due to declining soil fertility conditions. The region has observed a notable increase in cattle population through both local multiplication and importation from the neighboring Lango sub-region. Its geographical proximity to Nwoya district, which has recently documented FMD outbreaks, elevates the sub-county's epidemiological vulnerability to FMD transmission. The study engaged participants aged 18 years and above, stratified into three primary stakeholder categories: livestock keepers, cattle traders, and local administrative authorities.

1.6 Justification of Study

According to Baluka (2016), animal diseases represent the primary impediment to livestock production and trade development in Uganda. The prevalence of trans-boundary animal diseases, particularly Foot and Mouth Disease (FMD), significantly constrains the country's access to international export markets, rendering its participation in global livestock and livestock product trade negligible. The endemic presence of FMD necessitates frequent movement restrictions on livestock and their products during quarantine periods, substantially disrupting regional market dynamics and trading patterns.

FMD imposes substantial economic burdens on agricultural stakeholders through increased production costs, reduced investment incentives, and diminished agricultural outputs. As noted by Paton, Gubbins, and King (2018), FMD generates significant production losses that threaten food security and rural livelihoods through reduced milk yields, elevated disease control expenditures, and livestock mortality. Furthermore, Barratt et al. (2019) estimate that FMD contributes to a 30% annual reduction in livestock productivity across developing nations through restricted market access, international trade barriers, and diminished profit margins.

The implementation of enhanced FMD surveillance protocols in Koch Ongako Sub-county offers multi-sectorial benefits across public health, veterinary services, and agricultural industries. The anticipated significance includes:

i) Facilitation of rapid disease notification to veterinary and public health practitioners during initial FMD onset, enabling expedited control measure implementation and treatment access to minimize mortality rates.
ii) Enhancement of stakeholder collaboration within the agricultural sector, fostering integrated partnerships between farmers, traders, agricultural cooperatives, technical experts, and governmental authorities.
iii) Strengthening of livestock farming expertise and improving agricultural service delivery mechanisms to farming communities.
iv) Potential increase in national livestock productivity through strategic engagement of development partners, including NGOs, leading to enhanced economic outcomes for both governmental and agricultural stakeholders.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

This chapter reviews literature relevant to mobile phone–based surveillance of Foot and Mouth Disease (FMD) in cattle. It begins with an overview of FMD, followed by a discussion of surveillance methods, machine learning in disease detection, focusing on image analysis techniques, diagnostic algorithms, and performance metrics. Highlights research gaps, theoretical frameworks—Inter-Spread, Cambridge–Edinburgh, and Imperial models.

2.2 FMD Overview

FMD remains among the most highly transmissible viral diseases affecting cloven-hoofed animals, including bovines, porcines, caprines, ovines, and bubalines. The causative agent, Aphthovirus, is readily detectable in all infected animal secretions and excretions, including urine, saliva, feces, semen, milk, expired air, vesicular fluid, and aborted fetal tissue. The FMD virus demonstrates rapid reproduction and transmission dynamics within susceptible animal populations (Metwally et al., 2021).

Disease transmission occurs through both direct and indirect pathways. Direct transmission involves contact with infected animals, while indirect transmission occurs through exposure to contaminated environmental matrices containing infectious secretions and excretions. Aerosol transmission represents a significant epidemiological factor, particularly in favorable climatic conditions, enabling long-distance viral dispersion, especially over aqueous surfaces. Additionally,

humans can serve as mechanical vectors, facilitating viral transmission via contaminated footwear, clothing, or epidermal surfaces.

Clinical manifestations include characteristic vesicular lesions, predominantly localized to the pedal region, oral cavity, and mammary tissue of affected animals. Additional vesicular formations may present on the vulva, prepuce, and pressure points of the inter-phalangeal spaces. Vesicular rupture results in erosive lesions at affected sites, precipitating systemic manifestations including pyrexia, cachexia, depression, tremors, anorexia, lameness, and decreased lactation.

FMD is classified among the most significant impediments to international trade in livestock and animal products (Byaruhanga et al., 2017). The economic impact encompasses multiple parameters: lactation reduction, affecting both human consumption and calf nutrition, with potential losses reaching 33% in extensive outbreaks; diminished livestock growth rates and juvenile mortality (2-5%); reduced animal traction capacity, disrupting agricultural operations; and reproductive failures, with individual abortions imposing substantial economic burden on producers through extended nonproductive periods or necessitating premature culling.

2.3 Surveillance Methods

Effective epidemiological control and outbreak mitigation necessitate timely disease detection through sophisticated surveillance methodologies, particularly indicator-based surveillance (IBS) and event-based surveillance (EBS) systems (Mohanty et al, 2019). Indicator-based surveillance represents a conventional epidemiological approach, utilizing structured data streams comprising standardized disease reporting protocols from healthcare facilities and diagnostic laboratories to public health authorities. In contrast, event-based surveillance mechanisms leverage unstructured data matrices, including social media platforms, community-reported incidents, mass media communications, and digital information repositories for disease detection and epidemiological

monitoring. EBS methodologies typically operate within community-centric frameworks, deriving surveillance data from digital communication channels, including social media networks, health-related blogs, and electronic messaging systems (World Health Organization, 2014).

2.3.1 Traditional Approaches

Upon initial notification or detection of suspected FMD cases within a designated geographical locale, veterinary specialists conduct systematic physical examinations of potentially affected livestock populations through comprehensive kraal-to-kraal surveillance protocols. Animals exhibiting characteristic clinical manifestations undergo immediate isolation and quarantine procedures. Laboratory diagnostic methodologies serve dual functions: confirmation of preliminary clinical diagnoses and generation of critical epidemiological data, including viral serotype identification and strain characterization. However, these conventional surveillance methodologies present significant operational constraints, including temporal inefficiencies, diagnostic accuracy limitations, and resource allocation challenges, particularly in achieving definitive FMD confirmation.

2.4 Mobile Technology in Veterinary Medicine

Contemporary disease surveillance architectures increasingly incorporate real-time data analytics, leveraging diverse technological platforms and heterogeneous data sources to monitor infectious disease epidemiology. Traditional passive surveillance frameworks remain predominantly dependent on healthcare provider-mediated data transmission to public health authorities, presenting inherent temporal and operational limitations (Choi et al., 2016).

2.4.1 Related Existing Surveillance Systems

Information technology integration for digital data acquisition and processing has significantly enhanced infectious disease surveillance methodologies, facilitating rapid epidemic intelligence and timely identification of infectious disease outbreaks (Mohanty et al., 2019). Multiple surveillance systems have been implemented in veterinary medicine to address animal healthcare challenges. This analysis examines several prominent surveillance platforms:

i) AfyaData

AfyaData (Kiswahili for "health data") was developed by the South African Center for Infectious Disease Surveillance (SACIDS) in Tanzania following the Ebola outbreak (Fabre, 2019). Karimuribo et al. (2017) describe AfyaData as an open-source platform integrating mobile technology for digital disease surveillance at community and national levels. The system architecture comprises dual components: an Android-based mobile client and a web-based server application. The mobile client facilitates surveillance data collection, transmission, and feedback tracking across multiple hierarchical levels. The platform provides analytical visualization interfaces for health stakeholders to process data collected via the mobile application, enhancing disease outbreak detection and response capabilities in East and Southern Africa.

Operational Successes: Enhanced early detection of Ebola Virus Disease clinical manifestations at community levels and reduced administrative burden compared to traditional paper-based systems

Operational Limitations: Insufficient capacity for managing large-scale disease incidents due to traditional non-participatory methodologies, delayed official surveillance data transmission to sub-national and national authorities, inadequate feedback mechanisms for data collectors and limited capability for individual subject tracking and geographical location monitoring.

ii) EMA-i

The Event Mobile Application (EMA) represents an Android-based platform enabling veterinary personnel and livestock producers to collect, manage, and report disease outbreaks with real-time geospatial capabilities. The application integrates with the Food and Agriculture Organization's Early Warning System package, facilitating geo-referenced data collection and transmission to the Global Animal Disease Information System (EMPRES-i) database. This information dissemination framework encompasses communities, producers, veterinary personnel, and decision-makers, enhancing disease containment through critical data sharing (Dr. Fenteng Danso et al., 2013).

Operational Successes of EMA-i*:* Enhanced quantitative and qualitative parameters of animal disease reporting, Facilitated expedited decision-making protocols, Accelerated response capabilities to disease outbreak scenarios, Strengthened early warning surveillance mechanisms

Operational Limitations*:* Internet connectivity dependencies, restricted functionality parameters, Absence of wearable technology integration, Limited notification capabilities, Lack of independent data verification protocols, Resource-intensive temporal requirements

iii) LivHealth e-surveillance

Developed by Badili Innovations Ltd (Kenya) and implemented in 2020, this platform enables Community Disease Reporters (CDRs) and veterinary professionals to execute comprehensive disease surveillance protocols. The system facilitates collection, documentation, and digital transmission of animal health data to centralized servers, incorporating symptomatic presentations and geospatial parameters. Field veterinarians conduct subsequent data analysis and diagnostic assessments (Badili Innovations Ltd, 2020).

Operational Successes: Enhanced disease prevention and control accuracy metrics**,** Strengthened veterinary-pastoral communication networks**,** expanded livestock disease data acquisition channels**,** Implementation of targeted therapeutic interventions.

Operational Limitations: Insufficient veterinary expertise in field operations**,** inadequate diagnostic infrastructure**,** Potential sampling bias affecting population representativeness.

iv) Google Trends

Google Trends represents an open-access search analytics platform quantifying temporal search volume patterns relative to total query volumes within specified parameters. The platform aggregates data from multiple digital sources, including internet searches, social media platforms, blog content, and digital news repositories (Verma et al., 2018). The system employs real-time influenza surveillance through analysis of health-seeking behavioral patterns manifested in search queries, leveraging the substantial volume of health-related information searches (Nuti et al., 2014).

Operational Limitations: Reliability constraints for diseases with limited media coverage**,** Potential bias from media-driven rather than epidemiological patterns**,** Geographic and provisional disease pattern representation inadequacies (Cervellin, Comelli and Lippi, 2017)

v) ProMED-mail

Initiated in 1994 under International Society for Infectious Diseases (ISID) governance, ProMED-mail employs email-based surveillance for emerging/re-emerging diseases and toxicological events affecting human, animal, and plant populations. The platform integrates field expertise, professional networks, and local media reporting for near real-time disease emergence notifications. Expert moderators provide contextual analysis incorporating scientific literature references, with dissemination through email, web platforms, social media channels, and RSS feeds (Carrion, 2018).

Operational Limitations: Reliance on human moderators versus algorithmic analysis**,** Potential subjective bias in event significance assessment**,** Limited comprehensive epidemiological data provision**,** restricted case mortality documentation beyond primary source content.

This systematic review demonstrates the evolving landscape of digital disease surveillance technologies, highlighting both technological advancements and persistent operational challenges in veterinary epidemiology.

2.5 Machine Learning Applications

Machine learning encompasses a comprehensive suite of computational methodologies and algorithmic frameworks that enable autonomous system learning and adaptation. This technological domain represents a specialized application of Artificial Intelligence (AI), facilitating automated learning processes and performance optimization through experiential data acquisition, without explicit programming requirements (Alam, 2023).

Contemporary machine learning applications demonstrate significant penetration across diverse technological domains, including social media algorithm optimization, computer vision implementations, sentiment analysis (quantitative assessment of textual emotional valence), and natural language processing applications for inter-lingual translation systems.

2.5.1 Image analysis techniques

Image analysis encompasses computational methodologies employed for extracting quantifiable information from digital imagery through algorithmic processing tools that facilitate pixel segmentation based on chromatic or density parameters (Davis et al., 2021). This research implementation utilized multiple analytical techniques for digital bovine image processing:

Image Acquisition Protocol. Implementation of standardized photographic capture methodologies utilizing calibrated imaging systems.

Image Segmentation Analysis: Application of algorithmic transformations for object-specific segmentation, Conversion of captured imagery into discrete analytical components, Generation of representative object matrices.

Feature Extraction Methodology: Implementation of critical computational processes for object classification, Development of recognition algorithms for phenotypic characteristics, Extraction of diagnostically relevant morphological parameters.

Image Enhancement Protocol: Application of digital signal processing for feature accentuation, Implementation of contrast optimization algorithms, Enhancement of analytical visibility for diagnostic assessment.

2.5.2 Disease detection algorithms

Machine learning algorithms demonstrate significant applicability in disease detection protocols through comprehensive analysis of digitized imagery and medical documentation. The following section delineates principal machine learning algorithmic frameworks employed in veterinary disease detection methodologies:

i) Support Vector Machine (SVM) Algorithm

Support Vector Machines (SVMs) represent a supervised machine learning algorithmic framework optimized for classification and regression analytics. This methodology implements hyperplane optimization for multi-class data point segregation. SVMs demonstrate particular efficacy in computer vision applications, pattern recognition protocols, and natural language processing implementations (Awad and Khanna, 2015).

Relevance to FMD System: FMD presents as distinct visual lesions (blisters, ulcers, and erosions) on the mouth, feet, and teats of infected cattle. SVM can be trained on pre-extracted features from images (like color, shape, and texture of lesions) to classify images into FMD-positive vs. healthy cattle.

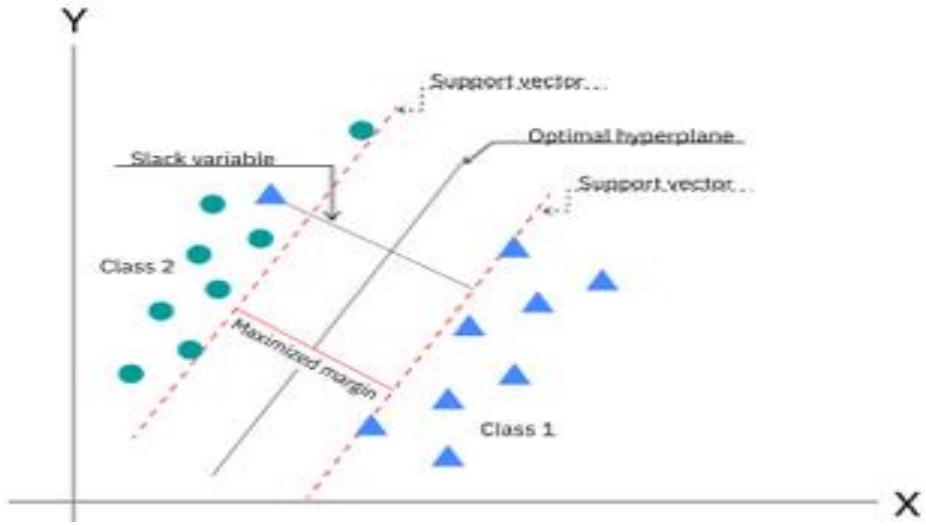


Figure 2 1*:* An illustration of Support Vector Machine (SVM) Algorithm (Adapted from Awad and Khanna, 2015)

ii) Random Forest (RF) Algorithm

Random Forest (RF) methodology, as described by Cutler et al. (2012), represents a supervised machine learning algorithmic framework utilizing labeled training data for pattern recognition and outcome prediction. This ensemble learning approach integrates multiple decision tree outputs to generate consolidated classification and regression analytics. The algorithm implements parallel decision tree computation, aggregating individual tree predictions to produce optimized classification and regression outcomes.

To illustrate the algorithmic mechanics: Consider a computational decision scenario involving ten distinct systems. The algorithm generates multiple decision trees (analogous to 100 independent evaluations), each providing classification output. The final classification is determined through majority voting mechanisms across the ensemble, optimizing predictive accuracy through collective decision tree analysis.

Relevance to FMD System. FMD symptoms are multifactorial and can be represented by many different image features (color intensity, lesion size, and shape irregularities). Random Forest aggregates predictions from many decision trees based on these features to determine if an image shows signs of FMD.

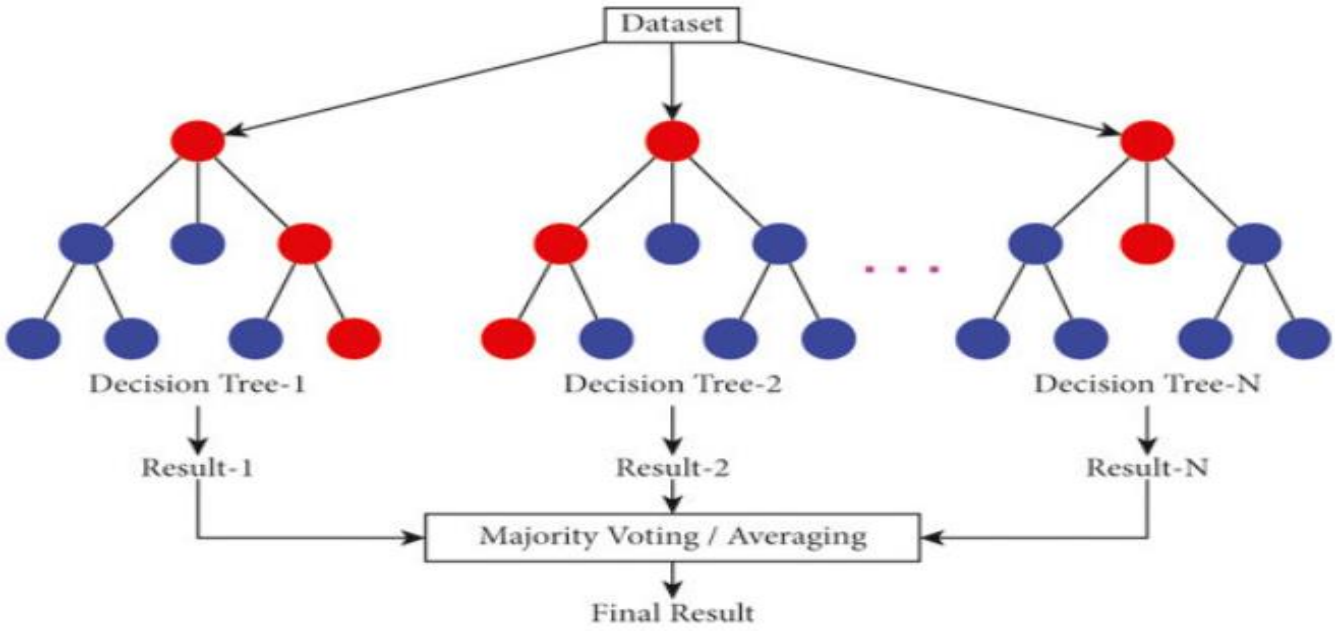


Figure 2 2*: *An illustration of Random Forest (RF) Algorithm (adapted from Cutler et al., 2012)

iii) Convolutional Neural Network (CNN) Algorithm

Convolutional Neural Networks (CNNs) represent sophisticated deep learning architectures that implement hierarchical image processing through weighted importance assignment to diverse

morphological features, facilitating precise object differentiation. The architectural framework comprises interconnected neural layers with standardized weight distributions, optimizing parameter efficiency during back-propagation training protocols. CNNs demonstrate particular efficacy in automated spatial information extraction from input imagery, facilitating concurrent feature extraction and image classification through self-optimizing algorithms (Ghaffar Nia et al., 2023).

Relevance to FMD System: CNNs are designed for end-to-end image classification. They automatically learn visual features (edges, textures, shapes) directly from FMD lesion images. CNNs can be deployed on mobile devices using TensorFlow Lite, enabling real-time detection of FMD in the field

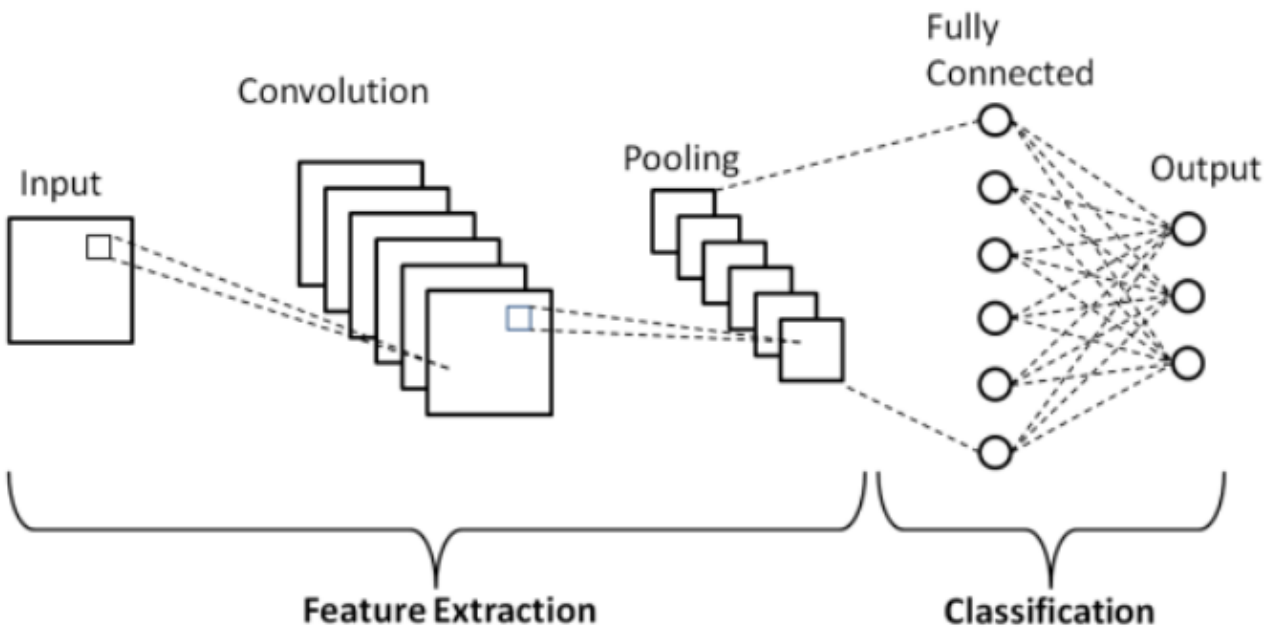


Figure 2 3**:** *An illustration of Convolutional Neural Network (CNN) Algorithm (Adapted from Ghaffar Nia et al., 2023)*

2.5.3 Performance metrics

This section describes the methodological framework used to evaluate the model's performance efficiency and effectiveness through multiple quantitative criteria and metrics (Powers, 2020). The study employed various performance metrics to systematically assess the machine learning model's predictive capabilities and operational reliability.

a) **Accuracy**: Accuracy represents a fundamental performance metric widely implemented in machine learning model evaluation, particularly in diagnostic applications. This metric quantifies a model's predictive precision by calculating the proportion of correct predictions relative to the total predictions generated. The accuracy metric is mathematically expressed as the ratio between correctly classified instances and the aggregate number of predictions, typically represented as a percentage. The computational formula for machine learning accuracy is: Accuracy = (Number of Correct Predictions / Total Number of Predictions) × 100%.

b) **Precision:** This metric evaluates the positive predictive value of a machine learning model by quantifying the proportion of correctly identified positive cases among all positive predictions. Mathematically, precision is expressed as the ratio of true positive predictions to the sum of true positive and false positive predictions (total positive predictions) generated by the model. This metric holds particular significance in diagnostic applications where false positive results could lead to adverse consequences, such as misdiagnosis in veterinary disease screening or erroneous disease outbreak alerts in agricultural surveillance systems.

c) **Recall:** This metric quantifies a machine learning model's sensitivity in detecting true positive cases within a diagnostic population. In epidemiological applications, recall is

mathematically expressed as the ratio of correctly identified positive cases (true positives) to the total number of actual positive cases in the population (true positives + false negatives). This metric holds particular significance in veterinary disease surveillance systems where false negative predictions could have severe consequences, such as missed early-stage disease outbreaks in livestock populations or undetected zoonotic transmission events in agricultural settings.

d) **F1 Score:** This composite metric represents the harmonic mean of precision and recall, providing a balanced assessment of a diagnostic model's performance in veterinary disease detection systems. The F1 Score synthesizes both precision and recall into a unified performance indicator, particularly valuable in epidemiological surveillance where disease prevalence may be asymmetric or where differential costs exist between false positive and false negative predictions. This metric proves especially critical in veterinary diagnostic applications where disease occurrence patterns are typically imbalanced, such as in emerging pathogen surveillance or rare zoonotic event detection within agricultural populations.

e) **Confusion Matrix:** This diagnostic evaluation framework presents a structured tabular representation for assessing machine learning model performance in veterinary disease detection systems. The matrix systematically categorizes predictions into true positives (correctly identified disease cases), false positives (incorrectly flagged healthy cases), true negatives (correctly identified healthy cases), and false negatives (missed disease cases). In veterinary epidemiological surveillance, this comprehensive evaluation tool enables detailed analysis of model diagnostic accuracy and identifies specific areas for algorithmic refinement, particularly crucial in early warning systems for emerging livestock diseases or zoonotic events.

2.6 Research Gaps

Despite extensive literature on Foot and Mouth Disease (FMD) epidemiology and surveillance, several critical knowledge gaps remain unresolved.

First, limited empirical evidence exists on the application of artificial intelligence and mobile phone–based image recognition in veterinary epidemiology in sub-Saharan Africa. While machine learning has been widely applied in human medicine, studies on livestock disease detection remain few and largely experimental, with no published evidence of deployment in Uganda's cattle sector (Karimuribo et al., 2017; Fabre, 2019).

Secondly, existing mobile surveillance systems such as AfyaData, EMA-i, and ProMED-mail were not designed specifically for FMD and do not incorporate image-based diagnostic capabilities. Their limitations such as dependence on human moderators, delayed feedback and poor adaptability to local epidemiological contexts highlight a gap in disease-specific, AI-enhanced surveillance tools (Carrion, 2018; Nuti et al., 2014).

Thirdly, there is insufficient research on the readiness and adoption capacity of rural livestock communities in Uganda to use AI-driven surveillance systems. Most prior studies focus on system development or outbreak mapping, but few have empirically investigated stakeholder willingness, digital literacy, and local integration pathways. (Byaruhanga et al., 2017).

Finally, there is a gap in literature connecting mobile-based community surveillance data with theoretical epidemiological models such as the Inter-Spread, Cambridge–Edinburgh, and Imperial models. No prior studies demonstrate how farmer-generated mobile data can be integrated into predictive models to enhance outbreak forecasting.

These knowledge gaps justify the present study, which contributes by (i) designing and testing an AI-powered mobile surveillance prototype specifically for FMD in Ugandan cattle, (ii) generating empirical evidence on stakeholder adoption potential, and (iii) demonstrating how mobile community data can inform epidemiological models for proactive outbreak control.

2.6.1 Mobile surveillance limitations

The implementation of mobile-based surveillance systems for veterinary disease monitoring presents several methodological and operational constraints that warrant careful consideration like:

Data Verification Challenges: Mobile data collection protocols face significant verification challenges, particularly in authenticating and validating epidemiological information transmitted through mobile devices in agricultural settings.

Access Disparities and Reporting Bias: Differential access to mobile technology and internet connectivity among agricultural communities introduces potential reporting bias, potentially affecting the representativeness of surveillance data across diverse geographical regions.

Socio-behavioral Factors: Population-specific behavioral patterns and social determinants significantly influence disease reporting practices, potentially impacting the completeness and timeliness of outbreak notifications within agricultural communities.

Laboratory Capacity Constraints: Limited diagnostic laboratory infrastructure may impede comprehensive disease confirmation processes, potentially compromising the integration of clinical and laboratory data in mobile surveillance systems.

Technical Capacity Development: The effective implementation of mobile surveillance systems necessitates systematic capacity building among veterinary personnel, ensuring proficient utilization of digital tools in disease monitoring protocols.

2.6.2 Technology integration needs

The optimization of veterinary disease surveillance systems necessitates comprehensive technological integration across multiple platforms and stakeholder networks. Critical integration requirements include:

Emergency Communication Infrastructure: Implementation of SMS-based alert systems for rapid dissemination of disease outbreak notifications to agricultural stakeholders, enabling real-time response coordination across affected regions.

National Surveillance Network Integration: Seamless interoperability with existing national veterinary surveillance frameworks, ensuring standardized data exchange protocols and unified epidemiological monitoring capabilities across jurisdictions.

Agricultural Application Ecosystem: Strategic integration with established agricultural management platforms (e.g., AgriApp), facilitating comprehensive data aggregation and synchronized disease monitoring across diverse technological interfaces.

Standardized Data Exchange Protocols: Development of robust APIs and data exchange standards to ensure efficient information flow between mobile surveillance systems and existing agricultural technology platforms.

2.6.3 Implementation challenges

The deployment of mobile-based surveillance systems in agricultural communities presents significant operational and technical challenges that require systematic consideration:

Diagnostic Infrastructure Limitations: The study region's limited diagnostic capabilities necessitate primary reliance on syndromic surveillance methodologies, which inherently present reduced diagnostic specificity and potential misclassification of disease events.

Stakeholder Response Dynamics: Insufficient feedback mechanisms within local governmental veterinary services may impede system adoption and sustainability, potentially compromising the long-term viability of surveillance implementation efforts.

Data Quality Assurance: Critical concerns regarding data integrity, including potential loss of epidemiological information and temporal delays in transmission, necessitate robust quality control protocols.

In regions with high internet penetration rates, web-based surveillance systems present distinct methodological challenges for accurate disease activity monitoring. Social media platforms facilitate extensive sharing of individual health experiences and perceptions, potentially introducing significant noise into epidemiological signal detection. The interpretation of user-generated content and search query frequencies requires careful consideration of potential biases and misclassification risks.

As noted by Choi et al. (2016), contemporary web-based surveillance systems operate on the premise that disease occurrence correlates with information-seeking behavior patterns in query data. However, this assumption requires careful validation within specific epidemiological contexts and consideration of potential confounding factors.

2.7 Conceptual Framework

This framework explains how mobile technology, artificial intelligence (AI), and stakeholder participation work together to improve the detection and control of Foot and Mouth Disease (FMD) in cattle. It connects the inputs (independent variables)**,** processes (intermediate variables)**,** and outcomes (dependent variables) within the context of a mobile surveillance system designed and developed using Rapid Application Development (RAD) methodology. It provides a visual and

descriptive guide showing how the proposed system contributes to early detection, reporting, and control of FMD outbreaks in Koch Ongako Sub-County.

The framework was built on three inter-related components: independent variables, intermediate processes, and dependent outcomes.

Independent variables: This represents the technological and user-related inputs that drive the surveillance process. These independent variables include: Mobile phone–based data collection (farmers and traders capturing and submitting images of suspected FMD cases), Integration of artificial intelligence and machine-learning algorithms for automated image analysis and classification and Stakeholder participation through community reporting and feedback mechanisms.

Intermediate variables: The variable describes the operational processes that occur once surveillance data are collected. These include data preprocessing, automated image classification, risk mapping, notification generation, and coordination between farmers, local leaders, and veterinary officers. These interactions transform raw field data into actionable epidemiological insights.

Dependent variables: In this study, they represents the expected outcomes of implementing the mobile-based surveillance system. They include improved disease detection accuracy, faster response and reporting time, enhanced stakeholder engagement, and ultimately reduced spread and economic impact of FMD within the community.

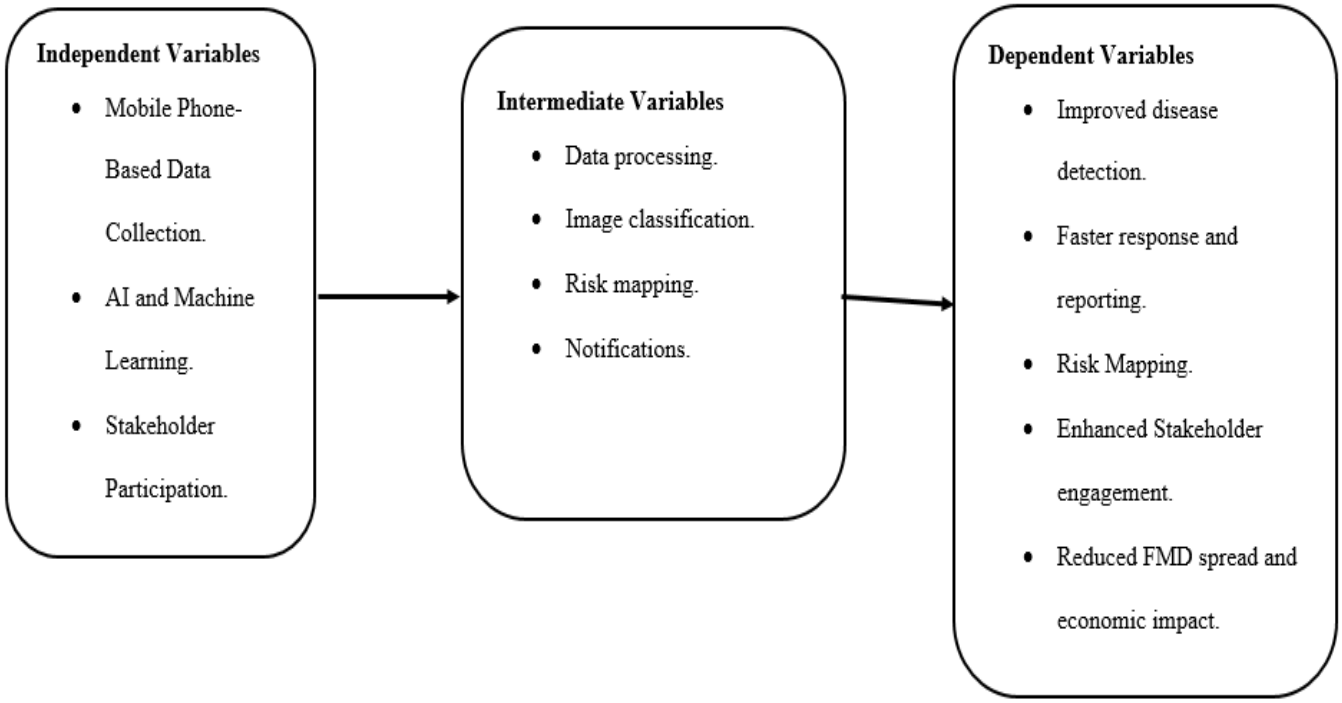


Figure 2 4: *Conceptual framework for mobile-based FMD surveillance*

Overall, the conceptual framework in **Figure 2.4** above, demonstrates that timely and reliable mobile data collection, supported by AI-driven analysis and active user participation, leads to more effective disease surveillance and control. The relationships outlined in the framework are based on empirical literature and the study objectives rather than any specific theoretical model.

CHAPTER THREE: METHODOLOGY

3.1 Introduction

This chapter presents the systematic methodological framework employed in conducting the research investigation. The methodology encompasses comprehensive protocols for research design, spatial-temporal parameters, population sampling strategies, data acquisition protocols, quality assurance mechanisms, and analytical frameworks. Specifically, the chapter delineates the research approach, investigative scope, experimental design parameters, geographical boundaries, population demographics, ethical compliance protocols, sampling methodologies, data collection instruments, quality control measures, variable operationalization, and statistical analysis procedures.

3.2 Research Approach

Research methodology selection follows systematic protocols for data acquisition, analysis, and interpretation, as established in epidemiological investigation frameworks (Creswell, 2014). The methodological approach is determined by the specific characteristics and requirements of the research objectives, particularly in the context of veterinary disease surveillance and intervention strategies.

This investigation employed a dual methodological framework incorporating both inductive and deductive approaches to epidemiological analysis. These complementary methodological paradigms enabled comprehensive investigation of disease transmission patterns and intervention efficacy.

3.2.1 Inductive Research Approach

The inductive methodological framework, also termed inductive reasoning, progresses from specific empirical observations toward broader theoretical generalizations. This methodological approach emphasizes pattern recognition through systematic observation, followed by theoretical framework development based on identified epidemiological patterns and hypothesis formulation.

In veterinary epidemiological investigations, inductive methodology permits flexible research trajectories, uninhibited by predetermined theoretical constraints at the investigation's onset. This approach, sometimes characterized as "bottom-up" analysis (Woiceshyn and Daellenbach, 2018), initiates with systematic data collection regarding the specified epidemiological parameters. Upon achieving sufficient data saturation, investigators transition to pattern analysis and theoretical framework development to elucidate observed disease transmission dynamics.

The methodological progression encompasses: Systematic data acquisition regarding specific epidemiological parameters, Pattern identification in epidemiological datasets, Theoretical framework development explaining observed disease transmission patterns and Generation of broader epidemiological propositions

While inductive methodologies offer valuable insights into disease transmission dynamics, conclusions derived through this approach maintain probabilistic rather than deterministic characteristics and remain subject to falsification through subsequent empirical investigation (Almalki, 2016).

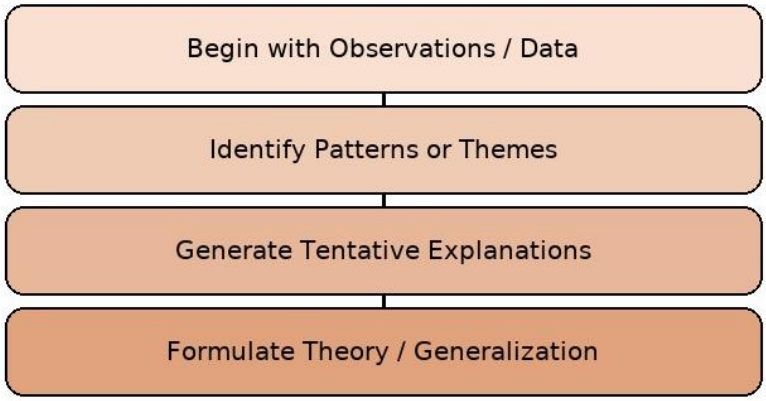


Figure 3 1: *Inductive Approach*

3.2.2 Deductive Research Approach

Deductive methodological frameworks initiate with established theoretical foundations from which specific hypotheses are formulated for empirical investigation. This systematic approach progresses from theoretical constructs through hypothesis testing to empirical validation, following a hierarchical analytical progression from general theoretical frameworks to specific epidemiological observations.

This methodological paradigm, characterized in epidemiological literature as "top-down" analysis, encompasses systematic review of existing theoretical frameworks and empirical investigations within the specified domain of inquiry. Investigators employing deductive methodologies conduct comprehensive literature reviews of relevant theoretical foundations and previous empirical investigations before proceeding to hypothesis formulation and testing protocols (Ali, 2017).

The deductive methodological progression encompasses: Theoretical framework identification, Hypothesis formulation based on established epidemiological principles, Systematic data

acquisition for hypothesis testing, Statistical analysis and empirical validation and Theoretical refinement based on empirical findings

In veterinary epidemiology, this approach facilitates systematic investigation of disease transmission dynamics through established theoretical frameworks while maintaining rigorous empirical validation protocols.

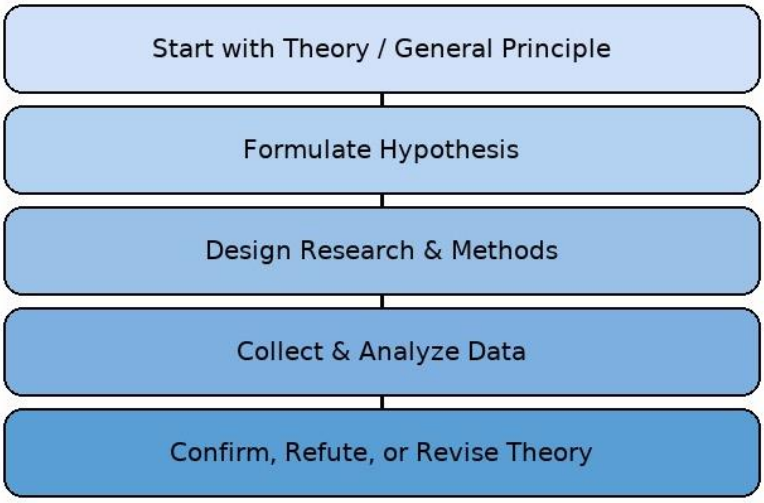


Figure 3 2: *Deductive Research Approach*

3.2.3 The Proposed Research Approach

This study adopted a Mixed Methods Approach within a Design and Development Research (DDR) framework. The approach combined both quantitative and qualitative techniques to support the design, development, and evaluation of a mobile-based surveillance prototype for Foot and Mouth Disease (FMD) detection in cattle. The DDR framework was chosen because it supports the systematic design, development, and evaluation of technological artifacts intended to solve real-world problems (Richey and Klein, 2014).

The quantitative component involved the collection of numerical data through structured questionnaires to assess stakeholders' technological readiness, smartphone ownership, and willingness to adopt the proposed system. Descriptive statistics were then used to analyze these data.

The qualitative component focused on gathering insights from cattle farmers, traders, and local leaders through open-ended responses and user feedback during prototype testing. This provided an understanding of user experiences, perceived usefulness, and challenges in adoption.

The Design and Development Research (DDR) approach guided the creation and testing of the mobile surveillance system. This approach is suitable for applied studies that seek to produce a functional technological artifact while addressing a practical problem.

Overall, this mixed-method approach ensured that both empirical data (quantitative) and contextual user experiences (qualitative) informed the design, refinement, and evaluation of the FMD surveillance prototype.

3.3 Research Design

The research design refers to the overall strategy and structure that guided the collection, analysis, and interpretation of data to achieve the study's objectives (Creswell and Creswell, 2018). In this study, a Descriptive Design within a Mixed Methods Design and Development Research (DDR) framework was adopted.

The descriptive component enabled the researcher to systematically document the characteristics, perceptions, and technological readiness of the target population i.e cattle farmers, traders, and local

leaders in Koch Ongako Sub-County. This helped in identifying patterns and relationships relevant to FMD surveillance practices.

The development component involved designing and building the mobile-based FMD surveillance system using the Rapid Application Development (RAD) methodology. This ensured that the prototype was developed iteratively with user participation and continuous feedback.

The integration of these components facilitated:

Systematic assessment of existing surveillance gaps through literature review and stakeholder consultation.

Development of a functional prototype incorporating machine learning (TensorFlow Lite) for image-based FMD detection.

Evaluation of the system's performance and user acceptance through quantitative and qualitative validation methods.

This design was appropriate for the study because it enabled the researcher to bridge theoretical understanding, empirical investigation, and technological innovation in a single coherent framework.

3.4 Software Development Methodology for FMD Surveillance App

Veterinary health surveillance systems provide essential infrastructure for disease trend monitoring, infection control protocols, and epidemiological risk analysis in livestock populations (Hernández et al., 2019). Methodological selection for mobile-based FMD surveillance requires systematic evaluation of data acquisition capabilities and technological implementation frameworks.

This investigation employed Rapid Application Development (RAD) methodological approach for mobile surveillance system development:

The selection and implementation of the methodological framework depends on specific research parameters, technological infrastructure requirements, and epidemiological surveillance objectives. Different investigative contexts may necessitate varied methodological approaches based on local surveillance requirements and technological capabilities.

3.4.1 Rapid Application Development (RAD) Software Methodology

Rapid Application Development (RAD) represents an iterative software development methodology emphasizing prototype refinement through systematic user feedback integration. This methodological framework facilitates accelerated development of mobile-based veterinary surveillance systems through iterative prototyping and continuous validation protocols (Mudassar et al., 2023).

When developing the Foot and Mouth Disease (FMD) detection app, RAD allowed the investigator to build, test, and improve quickly while involving farmers, cattle buyers, and local authorities. The RAD methodology encompasses four primary developmental phases:

i) Requirements Planning Phase

The requirement planning phase in RAD is the foundation of the entire development process. It involves identifying, analyzing, and prioritizing user needs before actual prototyping begins**.** Unlike traditional models that require exhaustive documentation, RAD emphasizes interactive discussions with stakeholders to quickly define the project's scope (Kumar and Kumar, 2019)

Relating the above phase to study, the researcher engaged the stakeholders (Cattle farmers, Cattle buyers and Local leaders) in the identification of the key needs such as simple tool that can scan animal images and provide immediate feedback on FMD symptoms, images of cattle to be used for the app, risk assessments among others. The local leader requested data aggregation for disease surveillance.

ii) Prototyping/User Design Phase

The development phase initiates creation of functional surveillance system prototypes adhering to established epidemiological requirements. Primary objectives focus on implementing core diagnostic functionalities while maintaining scalability for subsequent feature integration.

In context of this study, the researcher built the FMD app prototype quickly through designing the Add image button, Predict image button and text box for notification display. The app was tested to see if it correctly identifies symptoms from sample images and feed backs from users (Farmers, buyers and local leaders) were gathered to ensure usability of the app.

iii) Construction/Development Phase

Under this phase, the actual system was built. RAD emphasizes on rapid, iterative development, using prototypes and continuous user feedback. RAD unlike other traditional methods does not rely on full plan but builds the software incrementally.

The investigator developed the app's front end or user interface to facilitates uploading cattle images from the phone, displaying detection results for instance as "The animal is classified sick as it shows probable symptoms of FMD" OR "The animal is classified normal as it shows no probable symptoms of FMD". The app's back end was also developed for receiving uploaded images, sending images to the ML model for prediction and returning results to the frontend. The

ML Model was finally trained using TensorFlow using the images with FMD symptoms and those without.

iv) Cutover/Implementation Phase

The Cutover phase is the final stage of RAD, where the system moves from development to real-world use. It's also called the deployment phase. Unlike traditional methods, RAD emphasizes a smooth, fast transition, often while continuing to refine the app based on user feedback.

The investigator finally deployed the app to the actual users in the category of cattle farmers, buyers and local leaders. Final testing was done and feedback collected including training of users to ensure effective app usage.

3.4.1.1 Justifications of RAD Software Methodology

The Rapid Application Development (RAD) methodology was chosen in this study over other software development approaches such as the SCRUM and Waterfall Model because RAD emphasizes rapid prototyping, limited resource environments, and focused user feedback cycles all of which align closely with the objectives and constraints of this research project. Specific benefits of RAD are as discussed below:

RAD emphasizes continuous prototyping and quick iterations, allowing developers to produce working models early and refine them through direct user input. In contrast, Scrum requires structured sprints, sprint planning, and formalized team roles (Product Owner, Scrum Master, Development Team)**,** which were impractical within the scope of a single-researcher academic project.

RAD is highly adaptable to small, cross-functional teams with overlapping roles, making it ideal for an individual researcher collaborating with a few stakeholders or technical advisors. Scrum**,** by comparison, demands well-defined team roles and recurring sprint meetings that require a dedicated multi-member team for effective coordination (Schwaber and Sutherland, 2017).

The study required developing a functional prototype within a limited academic timeframe while ensuring adequate testing and validation. RAD's time-boxed phase like: requirements planning, user design, construction, and cutover enabled efficient project execution without the overhead of Scrum's sprint reviews and backlog refinements.

RAD's iterative model allows continuous engagement with end users throughout the development process. This direct communication helped integrate the practical needs of farmers and local authorities**,** ensuring that the final application reflected local realities such as intermittent connectivity and limited digital literacy. While Scrum also values user feedback, it typically channels it through the Product Owner and structured sprint reviews, which could delay integration of feedback in a single-developer context.

Alignment with Research Objectives. The goal of the research was to develop and validate a functional, user-centered prototype capable of detecting FMD symptoms using mobile imaging and machine learning. RAD's iterative prototyping model directly supported the scientific validation cycle design, test, refine, and re-test ensuring that the resulting system met technical requirements and user expectations within the academic period.

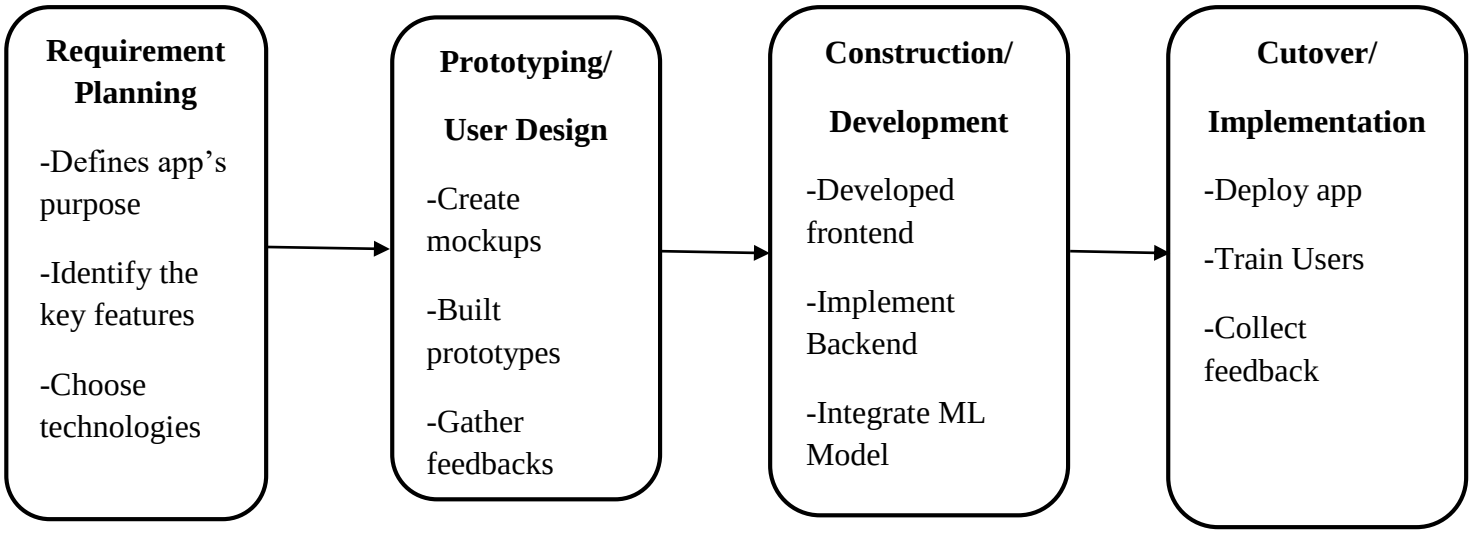


Figure 3 3**:** *An illustration of Rapid Application Development (RAD) Model*

3.5 System Scope

The developed system is a mobile phone–based surveillance application designed to support detection of Foot and Mouth Disease (FMD) in cattle. It incorporates machine learning models developed with TensorFlow Lite and runs on Android devices, which are widely used among the target population.

The system's functional scope includes: Capturing or uploading cattle images showing suspected FMD symptoms on the oral cavity, nasal passages, pedal tissues, and mammary glands; Automatic image preprocessing (resizing, enhancement, and feature extraction); On-device classification of images as either "Sick" (FMD-positive) or "Normal" (FMD-negative); Providing offline functionality to support use in rural areas with limited internet connectivity; and generating basic notifications to guide stakeholders toward appropriate veterinary intervention.

The system is limited to detecting visible clinical signs of FMD and does not provide laboratory confirmation or treatment recommendations.

3.6 Research Strategy

The research strategy outlines the systematic procedures adopted to achieve the study objectives through sequential and complementary stages. Guided by the Mixed Methods Design and Development Research (DDR) framework, this study employed a three-phase strategy integrating *exploration*, *design and development*, and *evaluation* phases (Hevner et al., 2004; Richey and Klein, 2014).

In the exploration phase, the researcher conducted a comprehensive review of existing surveillance systems and stakeholder consultations to identify operational gaps in current Foot and Mouth Disease (FMD) monitoring practices. This phase provided empirical and contextual understanding necessary for system conceptualization.

The design and development phase focused on creating a functional mobile-based surveillance prototype using the Rapid Application Development (RAD) methodology. Iterative prototyping and stakeholder feedback ensured that the system design addressed user needs and technical requirements (Kumar and Kumar, 2019; Mudassar et al., 2023).

Finally, the evaluation phase involved testing the developed prototype with end users: farmers, traders, and local leaders to assess usability, performance, and adoption potential. Quantitative data were analyzed statistically, while qualitative feedback was subjected to thematic analysis to validate system functionality and stakeholder acceptance (Creswell and Creswell, 2018; Nowell et al., 2017).

Table 3 1: *Research Strategy*

Specific Objective	**Research Method**	**Research Method Application**
To review existing surveillance systems for foot-and-mouth disease (FMD) in cattle populations to identify current capabilities and systematic gaps in disease monitoring.	1.Systematic Literature Review 2. Stakeholder Interviews using Questionnaires.	A structured review of scholarly articles, reports, and digital surveillance platforms (AfyaData, EMA-i, LivHealth, Google Trends, and ProMED-mail) was conducted to identify strengths and weaknesses. Supplementary semi-structured interviews with selected with stakeholders such as: cattle farmers, cattle traders and local leaders.
To develop and implement a mobile-based surveillance prototype integrating machine learning for the detection of FMD symptoms, addressing identified surveillance gaps and leveraging existing technological capabilities.	Design and Development Research (DDR). Rapid Application Development (RAD) Model.	The prototype was designed, built, and refined iteratively following RAD phases: requirements planning, user design, construction, and cutover. Stakeholder feedback from farmers and traders informed interface simplicity and offline functionality during each iteration (Kumar and Kumar, 2019; Mudassar et al., 2023).
To evaluate the performance and usability of the developed prototype through systematic engagement with key stakeholders, including livestock producers, traders, local administrative authorities and validation protocols	Quantitative and Qualitative Evaluation	The system was validated using both technical and user-based assessments. Quantitatively, model accuracy, precision, recall, and F1-score were computed to measure diagnostic performance. Qualitatively, feedback from end users was collected through questionnaires and analyzed thematically to assess usability, adoption willingness, and satisfaction (Nowell et al., 2017; Venkatesh et al., 2013).

3.7 Study population

The study population comprised livestock producers, cattle traders, and local administrative authorities in Koch Ongako Sub-County, Omoro District. Participant eligibility criteria included age ≥18 years and demonstrated knowledge of FMD surveillance practices.

The target population (N=155) was distributed across four parishes (Olabo, Lwala, Onyona, and Kal) and stratified as follows: livestock producers (n=68), cattle traders (n=68), and local authorities (n=19). A representative sample (n=46) was selected from this homogeneous population experiencing similar epidemiological challenges.

The category interviewed with questionnaire in this study were Cattle producers, Livestock traders and Local leaders in the proportion of: 20 Cattle Producers, 20 Cattle traders and 6 Local leaders who were stratified from the sample (n=46).

Cattle producers were interviewed because they are the primary livestock keepers and usually the first to observe clinical signs of Foot and Mouth Disease (FMD) in animals. Their participation helps capture ground-level realities of disease occurrence and reporting behavior.

Livestock traders were also targeted as they play a major role in animal movements, which are a critical pathway for the spread of FMD. Their insights help assess risks linked to markets and trade networks.

Local leaders this category were interviewed as they are central in community mobilization, communication, and enforcement of animal health regulations. They influence reporting and compliance with control measures.

3.8 Ethical considerations

The research protocol was approved by the Research Ethics Committee of Gulu University **Version 2.0, 2021-04-21** and received administrative clearance from the District Veterinary Officer (DVO) of Omoro District. Informed consent was obtained from all participants (livestock producers, traders, and local authorities) following comprehensive briefing on the study objectives. Data confidentiality was maintained throughout the research process. Animal welfare protocols were implemented to minimize livestock distress during field observations, adhering to standard veterinary practice guidelines.

3.9 Data Collections Methods

According to Muhammad and Kabir (2018), data collection comprises systematic procedures for gathering and quantifying information pertaining to research variables, enabling hypothesis testing and outcome assessment.

3.9.1 Questionnaires

The study employed structured questionnaires for primary data collection, facilitating quantitative analysis of stakeholder responses. This methodological approach enabled statistical analysis of participant perspectives. Note: The data collection instrument was implemented without pilot testing, as the research subject was determined to be familiar to the target population.

3.9.2 Sampling Strategies

Farm and animal selection utilized a systematic random sampling protocol. This methodology ensured unbiased selection probability across sampling units while optimizing population

representation. Data collection timing coincided with the cultivation period when livestock confinement practices facilitated comprehensive sampling access.

i) Sample size and sampling procedures

The study employed probability sampling across Koch Ongako Sub-County, targeting a population frame of 155 stakeholders. Sample selection utilized Excel-generated randomization to identify eligible participants comprising livestock producers, traders, and local authorities. Following Policy (2019) recommendations for finite populations, a 10% sampling fraction was implemented, yielding a final sample size of 46 participants stratified as follows: Livestock producers (n=20), Cattle traders (n=20) and Local administrative authorities (n=6). The random sampling protocol was selected for its methodological robustness and capacity to minimize selection bias while ensuring representative population coverage within the defined eligibility criteria.

Table 3 2: *Sample Size Distribution Frame/List*

Category	**Targeted Population**	**Sample**	**Percentage Representation**
Cattle Keepers	68	20	43.4
Cattle Buyers	68	20	43.4
Local Leaders	19	06	13.0
Total	**155**	**46**	**99.9**

ii) Sample Without Replacement

The study employed sampling without replacement methodology for participant selection. Under this protocol, once an individual was selected for inclusion in the sample, they were removed from the source population, eliminating the possibility of resampling and ensuring independence of observations.

3.9.3 Data Quality Control

The data security and integrity protocols implemented comprehensive safeguarding measures. Physical questionnaires were secured in locked storage facilities, while digital participant information was protected through password-encrypted systems. Data integrity was maintained through systematic backup procedures and regular malware scanning protocols. These multilayered security measures were implemented to ensure data confidentiality, integrity, and availability throughout the research process.

3.9.4 Measurements

The study employed a dual-source image acquisition methodology for the machine learning model's training and validation datasets. Primary data consisted of original photographic documentation of both FMD-affected and clinically normal cattle, while secondary data incorporated validated reference images from established databases. The image corpus specifically focused on documented FMD-susceptible anatomical sites: oral cavity, nasal mucosa, and pedal surfaces.

The surveillance application's architecture implements a user-interface-driven workflow where practitioners upload captured images for algorithmic analysis. The machine learning model employs computer vision techniques to analyze uploaded images against the trained parameter set, generating a binary classification output ("This animal was classified-Sick as it shows possible

signs of FMD"/" This animal was classified-Normal as it shows no possible signs of FMD") corresponding to FMD-positive and FMD-negative status respectively. The artificial intelligence component utilizes pattern recognition algorithms to evaluate morphological features characteristic of FMD pathology across the designated anatomical sites, comparing these against the validated training dataset parameters.

3.9.5 Data Analysis

The data analysis framework employed a mixed-methods approach. Quantitative data underwent systematic processing and digital entry for statistical analysis using SPSS (Statistical Package for Social Sciences) version 23 on a 64-bit Windows operating system. The analytical methodology incorporated both descriptive and inferential statistical techniques:

Quantitative analysis utilized descriptive statistics, generating frequency distributions and percentage tables to elucidate data patterns. Qualitative data underwent systematic thematic analysis aligned with the study objectives, incorporating triangulation with the quantitative findings to ensure comprehensive interpretation of results.

3.10 Image Acquisition

High-quality images of normal cattle were collected in the field using Hot infinix 10 phone equipped with 16MP camera and technical specification as: Resolution: 96 DPI, Dimensions: 100x200 - 300x500 pixels and Format: JPEG/JPG. Due to absence of active FMD cases during the study period, supplementary clinical imagery showing characteristic areas where FMD lesions are most visible (e.g., mouth, feet, and teats) were sourced from validated databases. Approximately 2000 images in equal proportion of sick and normal were used to train the model in this study.

The image acquisition protocol followed institutional authorization procedures: ICT Department clearance, University Research Ethics Committee approval, District Veterinary Officer authorization and Livestock owner informed consent.

3.11 Machine Learning Implementation

The machine learning component of this study was implemented by deploying a pre-trained model into a mobile-based surveillance application using TensorFlow Lite, Android Studio IDE, Kotlin, and XML**.** This ensured that the model could run efficiently on smartphones in field settings. The implementation process was systematic and involved four main stages: model conversion, mobile integration, user interface design, and system output.

3.11.1 TensorFlow Lite Conversion

The trained machine learning model was converted into the TensorFlow Lite (TFLite) format, which is optimized for mobile deployment. This process involved: Reducing model size through quantization to ensure faster performance, Optimizing computation for devices with limited memory and processing power and exporting the model as a .tflite file, ready for integration in the mobile application.

3.11.2 Integration in Android Studio

The TFLite model was integrated into the mobile application using Android Studio IDE, the official development environment for Android apps. Key steps included: Importing the .tflite model file into the Android project structure. Configuring build settings and dependencies to support TensorFlow Lite inference and Setting up classes and libraries to allow the app to communicate with the TFLite interpreter and process image inputs.

3.11.3 Application Logic Using Kotlin

The core application logic and functionality were implemented using Kotlin**,** the modern programming language recommended for Android development. Kotlin code was used to: Load the TFLite model into memory at runtime. Pass input data (preprocessed cattle images) to the model for inference. Capture the model output (classification as *"suspected FMD-positive"* or *"FMD-negative"*) and Trigger subsequent actions, such as generating alerts

3.11.4 User Interface Design Using XML

The application's user interface (UI) was designed using XML layouts in Android Studio. XML defined the visual structure of the app, including: Buttons for capturing or uploading images, Image **views** for displaying selected pictures, Text fields and labels for showing classification results and Alert prompts for notifying veterinary officers in case of suspected FMD-positive detections.

3.12 Validation Methodology

The validation framework implemented comprehensive testing protocols to ensure robust model performance in field conditions. The image dataset of 2,000 labelled images from primary field collection and validated secondary sources was partitioned to create independent training, validation and test cohorts to ensure an unbiased assessment of model generalization. Images were first grouped by source i.e field sources and secondary sources and by label (FMD-positive, FMD-negative).

Partitioning was performed using stratified random sampling so that class proportions and source composition were preserved across splits. To avoid information leakage, grouping was applied at the animal/session level where identifiers existed (i.e., all images from the same animal or capture

session were assigned to a single partition). The final split used for model development was 70% training, 15% validation, and 15% test.

The training set was used for gradient-based optimization and on-the-fly image augmentation (rotation, flip, small zooms) to reduce over fitting; the validation set guided hyper parameter selection and early stopping; the held-out test set was used only once for final performance reporting. Performance metrics reported on the test set include accuracy, precision, recall (sensitivity), F1-score, confusion matrix and inference time per image; confidence intervals for key metrics were calculated to reflect sampling variability. This three-way, stratified, animal-level partitioning ensures robust and reproducible evaluation of the TensorFlow Lite model under field-like conditions.

3.13 Performance Evaluation

The research implemented comprehensive evaluation protocols to assess the mobile surveillance system's efficacy across multiple operational parameters. The evaluation framework encompassed quantitative performance metrics, computational efficiency assessments, and stakeholder feedback analysis.

Model Performance Analysis: The validation methodology incorporated established epidemiological metrics to evaluate diagnostic accuracy. The analytical framework utilized precision measurements to assess diagnostic specificity, recall metrics for detection sensitivity, and F1 score calculations to determine balanced classification performance. These quantitative indicators provided robust assessment of the model's predictive capabilities in field conditions.

Computational Efficiency Assessment: System performance analysis demonstrated optimal computational efficiency in critical operational parameters. The application exhibited rapid

initialization characteristics and demonstrated efficient image processing capabilities. Real-time analytical processing facilitated immediate diagnostic feedback, enhancing the system's utility in field deployment scenarios where rapid assessment holds particular importance for disease control interventions.

Stakeholder Validation Analysis: Field validation protocols incorporated comprehensive stakeholder feedback mechanisms, particularly focusing on practical implementation efficacy. Agricultural stakeholders reported favorable assessments regarding the system's operational capabilities in live animal evaluations. The technological implementation demonstrated promising potential for integration into existing veterinary surveillance frameworks, with positive feedback regarding its practical application in agricultural settings.

This systematic evaluation framework provides strong evidence supporting the feasibility of mobile-based veterinary surveillance systems, while establishing quantitative benchmarks for future technological implementations in agricultural disease monitoring. The integration of performance metrics, computational efficiency assessments, and stakeholder validation demonstrates the potential for enhanced disease detection capabilities in resource-limited agricultural environments.

CHAPTER FOUR: FIELD STUDY RESULTS

4.1 Introduction

This chapter presents the findings of the study on the development and evaluation of a mobile phone–based surveillance system for Foot and Mouth Disease (FMD) in cattle within Koch Ongako Sub-County, Omoro District. The purpose of this chapter was to demonstrate how the research objectives outlined in Chapter One were addressed through both quantitative and qualitative data analysis. The chapter was organized into: Demographic and technological profile of the respondents highlighting key factors such as gender, education level, and smartphone ownership, which influence system adoption. Second, the results of the image analysis and machine learning implementation are presented, with emphasis on the system's detection accuracy and computational efficiency. Third, user experience data are analyzed to capture perceptions of usability, accessibility, and trust in the mobile surveillance system. Fourth, qualitative insights from farmers, cattle traders, and local leaders are discussed to provide a community-based perspective on the benefits, challenges, and expectations associated with the innovation.

4.2 Quantitative Analysis

4.2.1 Demographic and Technological Profile of Respondents

Appreciation of the demographic and technological characteristics of respondents was essential for interpreting the feasibility of adopting a mobile phone–based surveillance system for FMD. The researcher administered questionnaires to 46 participants comprising cattle buyers, cattle keepers and sub county local leaders in Koch Ongako and the results was analyzed both quantitatively and qualitatively. The data were processed using (SPSS) Statistical Package for the Social Sciences version 23, for 64 bits windows operating system. Statistical analysis of the findings was done using

frequencies and percentages tables. In line with the Specific objectives of the study, data were analyzed under the following sub-headings: questionnaire return rate, respondents' background information, Investigating Surveillance systems on foot and mouth disease in cattle, designing a mobile phone surveillance app for foot and mouth disease in cattle and evaluation of the proposed system by engaging stakeholders.

4.2.2 Gender Distribution of Respondents

The study revealed a relatively balanced gender representation, with both male and female stakeholders actively involved in cattle keeping and trading. However, **Table: 4.1** shows a large disparity of gender distribution in favor of male respondents in Koch Ongako Sub County. It was established that 84.4% Respondents were male and only 13.3% were female. This implies that most of the Cattle keepers, Cattle buyers and Local leaders were males in the study location. This finding implies that while both genders are potential users of mobile surveillance systems, training and sensitization efforts may need to consider gendered differences in access and usage of mobile technologies

Table 4 1: *Gender Distribution of the Respondents*

Respondent's Gender

Gender	Frequency	Percent	Valid Percent
Male	38	84.4	86.4
Female	6	13.3	13.6
Total	44	97.8	100.0

Source: SPSS

4.2.3 Education Levels of Respondents

Respondents reported varying levels of formal education, ranging from primary to advanced education. **Table: 4.2** indicates that most of the respondents in this study attained some education with 20% who sat for PLE, 40% UCE, 37% UACE respectively. This therefore implies that most of them are literate which made the whole data collection process smooth as they were able to understand the research topic and filled the questionnaire with ease and able to engage with mobile phone–based technologies.

***Table 4 2**: Education Level of the Respondents*

Respondent's Level of Education

Education Level	Frequency	Percent	Valid Percent
PLE	9	20.0	20.5
UCE	18	40.0	40.9
UACE	17	37.8	38.6
Total	44	97.8	100.0

Source: SPSS

4.2.4 Smartphone Ownership and Usage

The researcher engaged the respondents to ascertain whether they possess mobile smart phones and if they knew how to use it efficiently. The result showed that about 29 participants who constituted 64.4% of the respondents agreed that they possess mobile smart phones and 27 participants that made up 60.0% of them admitted that they could indeed use mobile smart phones quite effectively. This high ownership rate is consistent with increasing mobile penetration in rural Uganda and supports the feasibility of the surveillance system as represented in the **Figure 4.1** and **Figure 4.2** below.

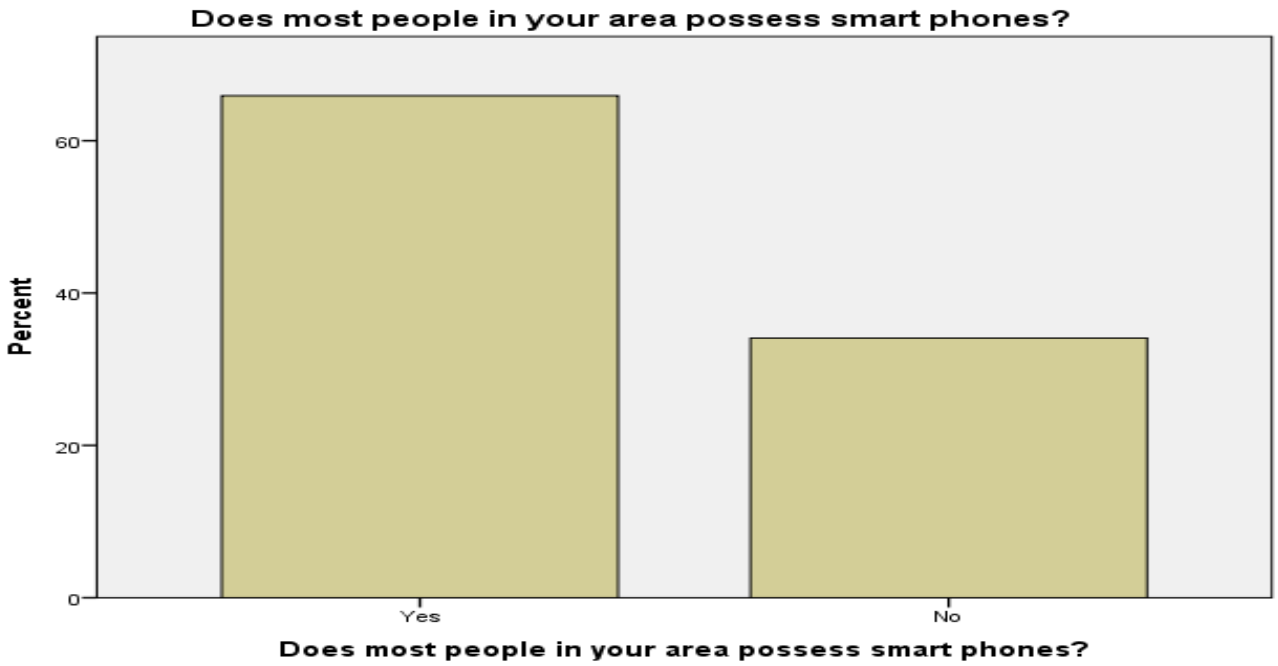


Figure 4 1: *Percentage of participants who have smart Phones*

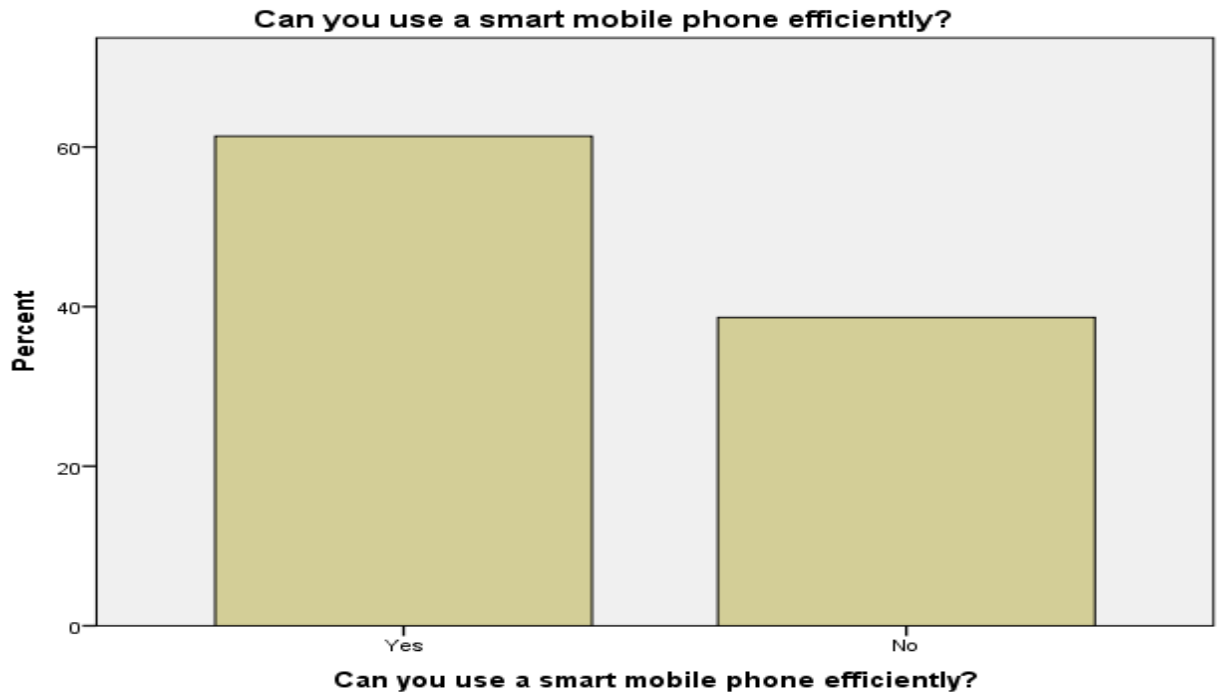


Figure 4 2: *Percentage of Participants who can use smart phone efficiently*

4.2.5 Awareness of Roles in Surveillance

The researcher tasked the stakeholders to identify whether they had a role to play in the surveillance of foot and mouth disease. The study found that 61.4% of respondents recognized their role in FMD surveillance, while 38.6 % were less aware as represented in **Table 4.3** below. This strong awareness indicates readiness among most farmers and traders to engage with surveillance systems, especially when benefits such as disease control and prevention of cattle loss are clear. However, the minority with low awareness suggests that sensitization campaigns are needed to ensure universal participation.

Table 4 3: *Participants who are aware that they had roles to play in Surveillance of FMD*

Are you aware that you have role to play in surveillance of FMD?

Responses	Frequency	Percent	Valid Percent
Yes	27	60.0	61.4
No	17	37.8	38.6
Total	44	97.8	100.0

Source: SPSS

4.3 Image Analysis and System Performance

The image analysis was carried out using the developed mobile-based surveillance system for Foot and Mouth Disease (FMD). The aim was to evaluate the model's ability to correctly classify cattle images as either symptomatic or non-symptomatic, thereby assessing its diagnostic accuracy and reliability.

4.3.1 Image Analysis Results

The prototype presented comprehensive analysis capabilities through systematic evaluation of detection outcomes and error characterization.

System Generated Sample Detection

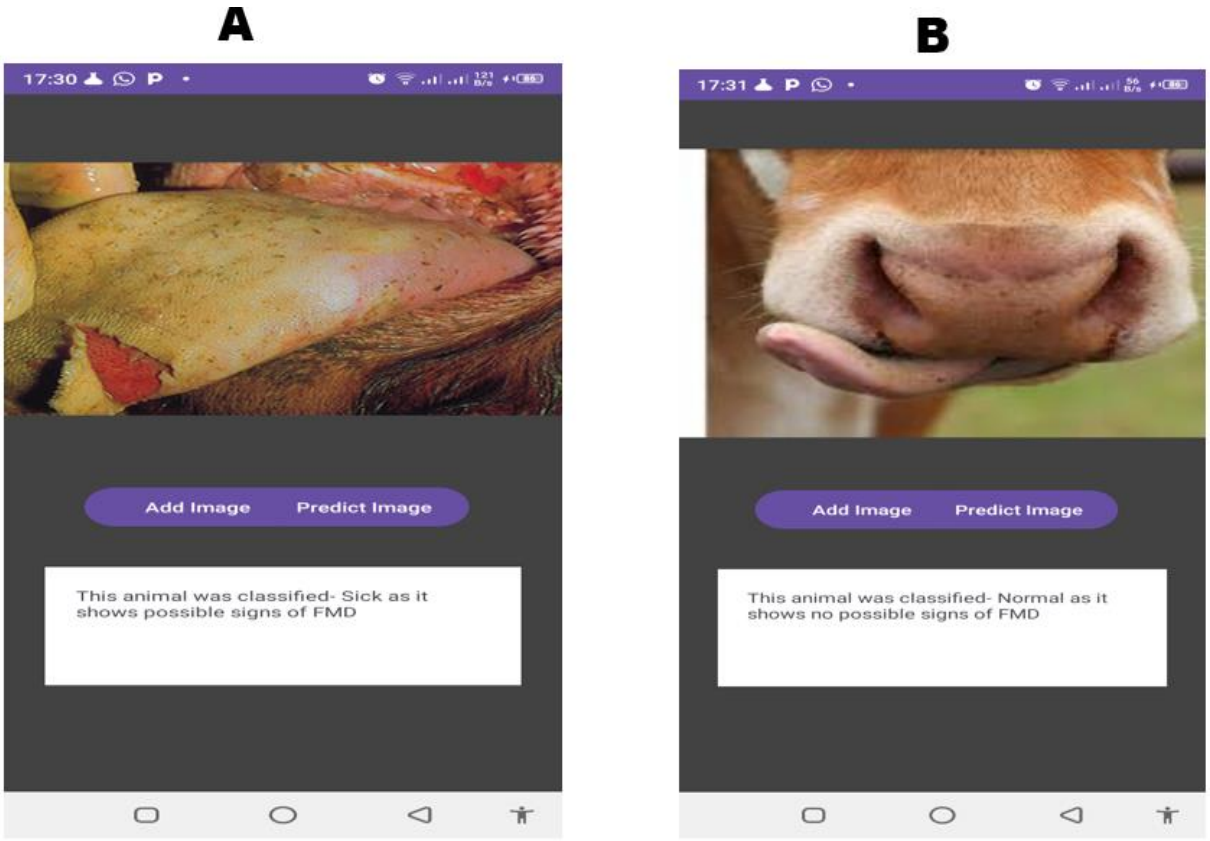


Figure 4 3: *Sample Image Detection*

The analytical framework demonstrates binary classification outcomes through representative case studies, illustrated in **Figure 4.3**. The detection protocol exhibits distinct diagnostic pathways:

Case A: Sick (Positive FMD Detection). The model demonstrated positive pathological identification, generating "sick" classification output upon image analysis and prediction protocols. This outcome reflects successful detection of characteristic FMD manifestations within the analyzed imagery.

Case B: Normal (Negative FMD Detection). The analytical framework correctly identified non-pathological presentations, generating "normal" classification outputs. This demonstrates the model's capability to differentiate between healthy tissue presentations and disease manifestations.

4.3.2 Error Analysis and Limitations

The basis of error analysis was the comparison between the system's classification results and expert-labeled ground truth. Errors arose from misclassifications i.e. false positives and false negatives produced by the TensorFlow Lite model during inference. These errors were influenced specifically by images not incorporated in the original machine learning training and validation, poor quality (blurry, low lighting, obstructions) or when lesions resembled other conditions (e.g., wounds not caused by FMD).

There are instances of limitations through documented error cases, where the model generated false positive "sick" classifications for novel imagery outside the training dataset. This finding holds particular significance for field implementation protocols, indicating the necessity for: Comprehensive training dataset development, Rigorous image standardization protocols and clear operational guidelines regarding appropriate input imagery

These findings emphasize the importance of standardized image acquisition protocols and systematic model training procedures in veterinary surveillance applications. The research suggests potential pathways for enhanced diagnostic reliability through expanded training datasets and refined classification algorithms.

4.3.3 System performance

Table 4 4: *System Performance Metrics*

Matrix	Value	Benchmark	Improvement
Accuracy	0.91	0.92	5/5
Detection Time	44s	46s	13s/step
False Positives	0.35	0.365	Retraction
User Rating	7/10	9/10	

The research findings demonstrate nuanced performance characteristics across multiple evaluation domains, warranting detailed analytical consideration:

Diagnostic Accuracy Assessment: The model's performance metrics demonstrated 91% accuracy as in ***Table 4.4*** above which is slight deviation from established benchmarks, attributable to the implementation of rigorous validation protocols. The methodological decision to partition datasets into discrete validation and training cohorts reflects established machine learning practices, ensuring robust evaluation of diagnostic capabilities while maintaining analytical integrity.

Computational Efficiency Analysis**:** The system demonstrated superior temporal performance characteristics compared to benchmark standards, primarily attributed to the implementation of optimized MobileNet2 architecture and efficient image processing protocols. This enhanced

computational efficiency holds particular significance for field deployment scenarios where rapid diagnostic response is essential for effective disease surveillance.

***False Positive Rate Evaluation*:** The training phase analysis revealed a 35% false positive rate in FMD classification, indicating specific instances where normal physiological presentations were incorrectly identified as pathological. This finding highlights areas for potential model refinement while maintaining acceptable diagnostic specificity for field implementation.

Stakeholder Acceptance Analysis: Quantitative assessment of user acceptance metrics demonstrated favorable outcomes, with 70% of stakeholders expressing positive evaluation of the mobile surveillance system. This high acceptance rate suggests promising potential for technological integration into existing veterinary surveillance frameworks, particularly in agricultural settings where rapid diagnostic capabilities are essential.

These findings provide crucial insights into the system's operational capabilities while identifying specific areas for continued optimization in veterinary surveillance applications. The comprehensive evaluation framework demonstrates the potential viability of mobile-based disease detection systems in agricultural settings, while maintaining rigorous analytical standards in performance assessment.

4.4 User Experience and Satisfaction

Ease of Use Assessment: Analysis of data presented in **Table 4.4** indicates that 70% of participants (7 out of 10) reported the model demonstrated high usability characteristics.

Implementation Evaluation: Comparative analysis revealed that 80% of users found the application's implementation process more straightforward than existing surveillance systems.

Adoption Metrics: The study found near-universal willingness among agricultural practitioners to adopt the technology, citing rapid disease detection capabilities and intuitive interface design as primary motivating factors.

4.4.1 User Satisfaction Metrics

Usability Performance: Quantitative analysis demonstrated that 78% of participants (36 out of 46) reported favorable usability scores, attributing their assessment to the application's streamlined functionality and focused feature set.

Feature Assessment: Detailed feature analysis revealed that 65% of respondents (30 out of 46) reported comprehensive understanding of the model's capabilities, providing valuable insights for future iterative improvements.

Aggregate Satisfaction Index: The study found that 86% of users (40 out of 46) expressed satisfaction with the model's performance, indicating successful alignment with user requirements and expectations.

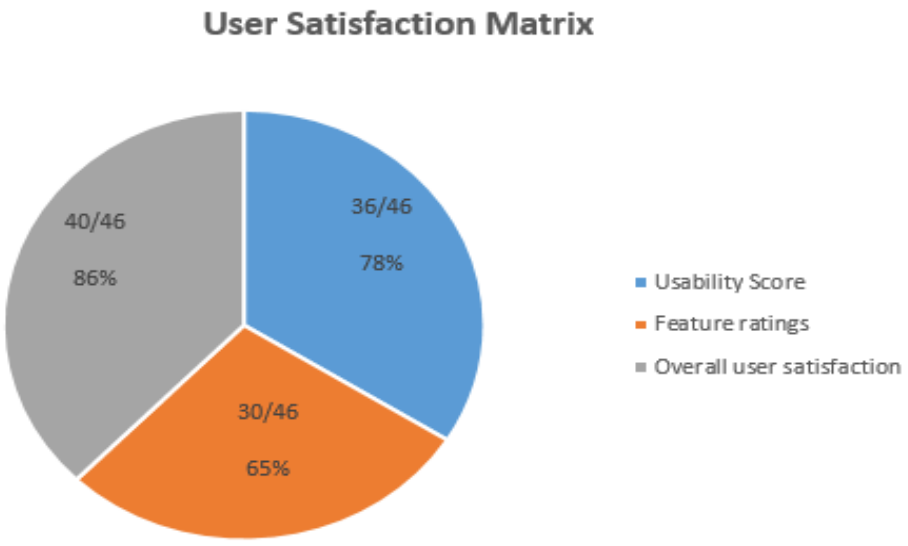


Figure 4 4: *User Satisfaction Metric*

4.5 Qualitative Findings from Stakeholders

In addition to the quantitative results discussed above, qualitative data from stakeholder interviews and questionnaire responses provided deeper insights into community perceptions of mobile-based surveillance for Foot and Mouth Disease (FMD). Three major themes emerged: **Perceived benefits of the system, challenges to adoption, and expectations for future improvement.**

4.5.1 Perceived Benefits of the Mobile Surveillance System

Farmers consistently emphasized that the mobile application would save time and reduce dependence on veterinary officers who are not always readily available. Many respondents noted that the ability to upload cattle images and receive instant feedback created a sense of empowerment and control.

One farmer from Lwala Parish remarked:

"In the past, we had to wait for the veterinary officer to visit our village, sometimes after several days. With this phone application, I can know immediately if my cow is sick, and I don't risk losing the whole herd."

Cattle traders also recognized the system's value in minimizing financial losses. They pointed out that knowing the health status of animals before transactions increased trust between buyers and sellers. Local leaders highlighted the potential of the application to support rapid reporting during outbreaks, thereby improving coordination with district veterinary authorities.

4.5.2 Challenges to Adoption

Despite general enthusiasm, respondents acknowledged challenges that could hinder adoption. Some farmers expressed limited confidence in their ability to use smartphones effectively,

especially older community members with low digital literacy. Others raised concerns about unreliable electricity and internet connectivity in rural areas, which could prevent timely reporting.

A cattle trader from Olabo noted:

"The application is good, but in my village we struggle with poor network. Sometimes we climb a hill to get signal. If the app cannot work offline, then many farmers may fail to use it."

These challenges highlight the need for training, user-friendly design, and offline functionality to ensure inclusivity.

4.5.3 Expectations for Future Improvement

Stakeholders expressed strong interest in expanding the system's functions beyond FMD detection. Farmers suggested including additional cattle diseases such as lumpy skin disease and East Coast fever, which also threaten livelihoods. Local leaders recommended linking the application to government and NGO programs so that data collected from farmers could trigger immediate veterinary interventions and possible compensation for losses.

One local leader observed:

"If the system can directly alert the District Veterinary Officer and the Ministry, then farmers will see more benefit. It should not just tell us that our animals are sick, but also connect us to help."

CHAPTER FIVE: FMD SURVEILLANCE MODEL DEVELOPMENT

5.1 Introduction

This chapter presented the design, development, and implementation of the Foot and Mouth Disease (FMD) mobile-based surveillance prototype. The prototype was developed using the Rapid Application Development (RAD) methodology outlined in Chapter Three, which emphasizes iterative design, stakeholder feedback, and rapid prototyping. The chapter details the prototype architecture, system components, functional modules, and process flow, as well as how the prototype addresses the research objectives.

5.2 Prototype Design Approach

The prototype was developed through four main RAD phases: Requirement planning, User design, Construction, and Cutover as discussed at length in **Section 3.4.1.**

Requirement Planning: Through field survey, data from cattle keepers, traders, and local leaders (Chapter Four) were used to define functional needs such as image capture, disease detection, and real-time feedback.

User Design: Involved creating Case diagrams, and process flow models diagrams, workflows were created to illustrate how the system would function.

Construction: This was carried out using Android Studio, TensorFlow Lite, Python frameworks and SQLite.

Cutover: This stage involved initial testing and validation were conducted with end-users in Koch Ongako Sub-County.

The design of this prototype was first drawn on paper with more enhancement made and represented in a use case diagram and process flow diagram.

5.3 Prototype Architecture

5.3.1 Use Case Diagram

The system was modeled using a use case diagram to show the interaction between the user and the mobile application.

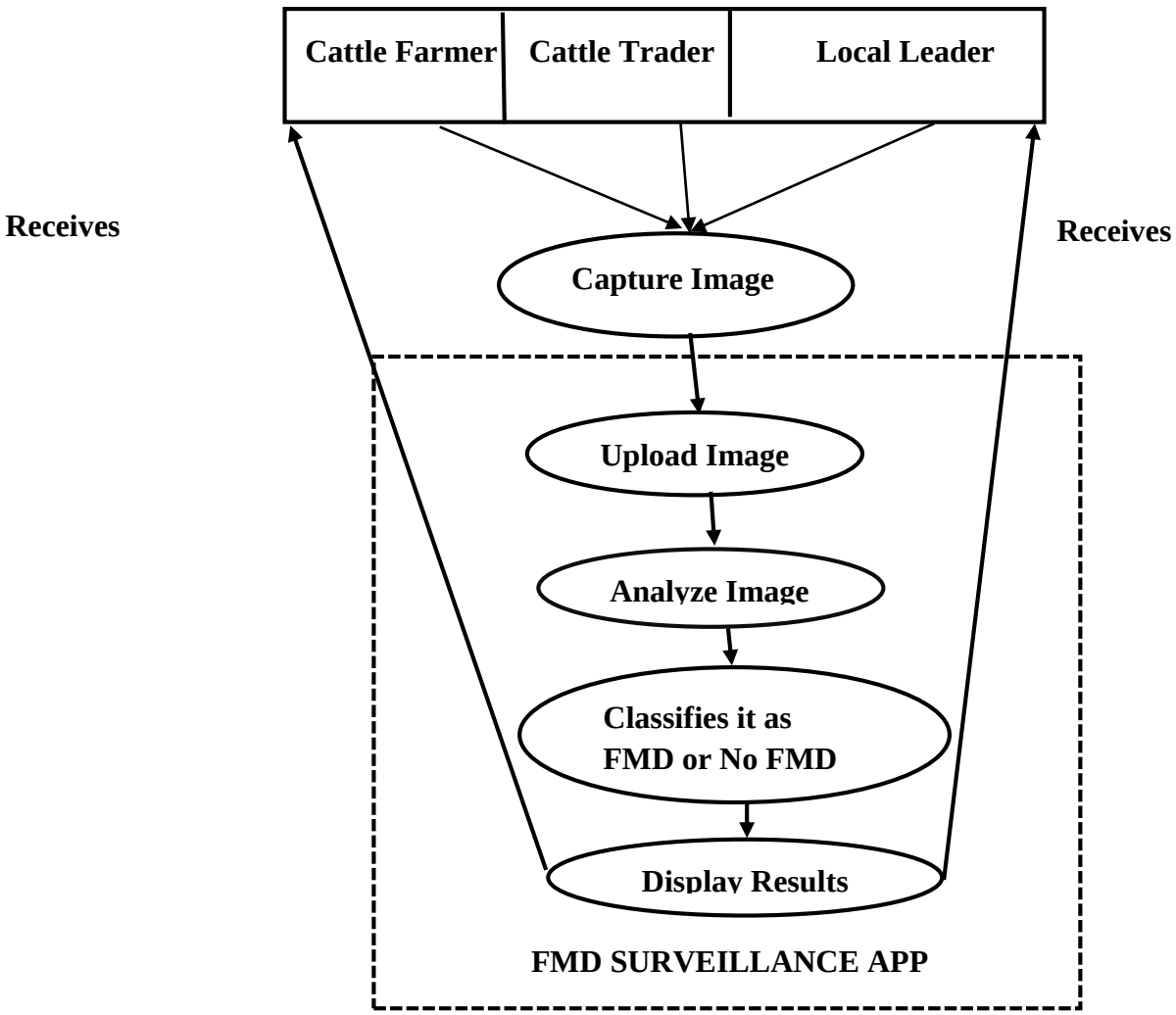


Figure 5 1: *A Use case diagram for the Prototype*

Main Use Cases (Functions)

Capture Image – Farmer/Trader/Local Leader takes cattle photo.

Upload Image – Farmer/Trader/Local Leader sends image to system.

Analyze Image – System classifies as "FMD" or "No FMD."

Display Result – System provides immediate feedback to Farmer/Trader/Local Leader.

Receives notifications – Farmer/Trader/Local Leader are notified.

5.3.2 System Process Flow

The logical process flow demonstrates how a cattle image moves from acquisition to classification and reporting.

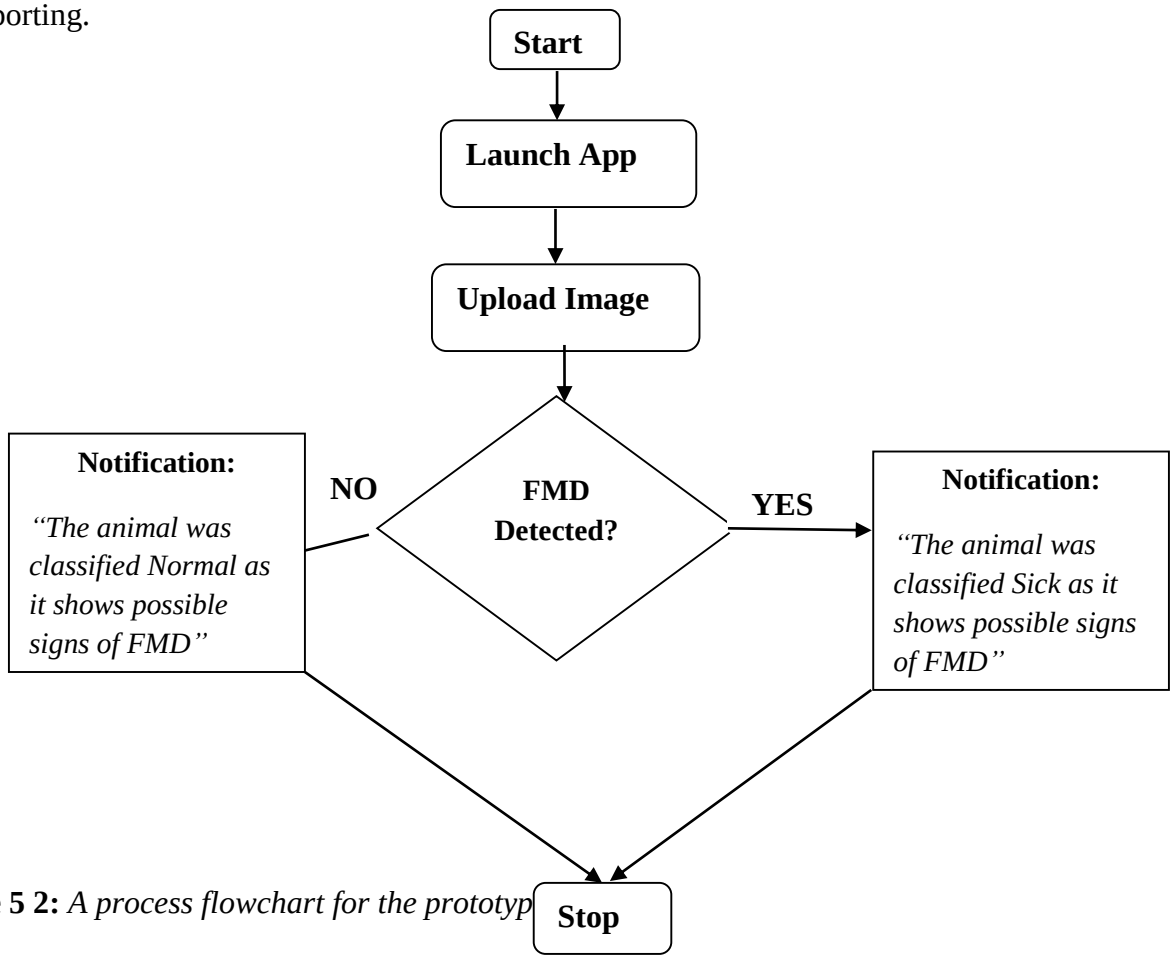


Figure 5 2: *A process flowchart for the prototyp*

5.3.3 Hardware Requirements

The development of the Foot and Mouth Disease (FMD) surveillance prototype depended on appropriate hardware to ensure smooth operation. Since the target users (farmers and traders) operate in resource-constrained environments, the prototype was designed to run on low-cost but reasonably capable devices. Major hardware requirements included:

Computer/Laptop. The computer played a central role in the development of the Foot and Mouth Disease (FMD) surveillance prototype. While the final system was deployed on mobile devices for field use, the initial design, model training, and application development required a workstation with sufficient computational resources. The computer was running on Windows 10 with Intel Core i5 Processor, 8 GB RAM and 500 GB storage capacity.

Smartphone with Camera. An Android smartphone, Infinix Hot 10 with 8 GB RAM and 16 megapixel camera resolution was required for capturing clear images of cattle. Image quality significantly influences the accuracy of the disease classification model, since blurred or low-resolution images can lead to misclassification.

Other hardware requirements were USB cables used for transferring the app from the Laptop to the phone and photos from phone to laptop for training. Including reliable power infrastructure.

5.3.4 Software Requirements

The successful development of the Foot and Mouth Disease (FMD) mobile-based surveillance prototype relied on a range of software tools and platforms. These were used for coding, machine learning model training, mobile interface design, data management, and deployment. The software requirements included:

Operating System

The prototype was developed on a workstation running Windows 10 and this was due to its compatibility with Android Studio, Python, and TensorFlow frameworks. It too provided a user-friendly environment for coding and project management.

Development Environment

The core application development was carried out using:

Android Studio IDE (Integrated Development Environment): This provided tools for coding in Java and Kotlin, debugging, compiling the app, and deploying it on smartphones. The research settled for android studio because all the farmers interviewed were confirmed to be using android phones.

Emulator Tools: Android Studio's built-in emulator was used to simulate how the prototype would run on different Android devices before field deployment.

Programming Languages

Java/Kotlin: Was used for developing the mobile app interface and business logic.

Python: Was used for machine learning model training, image preprocessing, and exporting the trained model into TensorFlow Lite format.

Machine Learning and AI Frameworks

TensorFlow and TensorFlow Lite: TensorFlow was used for training the FMD detection model on cattle images. The trained model was later converted to TensorFlow Lite format to allow lightweight, on-device processing on Android smartphones. The app in development was transferred to the mobile phone using a USB cable. **Figure 5.4** below shows TensorFlow model lite maker library interface with a sample code.

```
import os

import numpy as np

import tensorflow as tf
assert tf.__version__.startswith('2')

from tflite_model_maker import model_spec
from tflite_model_maker import image_classifier
from tflite_model_maker.config import ExportFormat
from tflite_model_maker.config import QuantizationConfig
from tflite_model_maker.image_classifier import DataLoader

import matplotlib.pyplot as plt
```

Figure 5 3: *Tensor-Flow model lite maker library interface*

Figure 5.3 above shows how TensorFlow lite model maker library was imported and trained on the labeled images of the cattle with or without foot and mouth disease uploaded using the Data Loader. The model is then quantize and exported to a downloadable format for integration in the android code.

The model is connected to the interface using Kotlin codes as shown in the **Figure 5.4** below.

```kotlin
val model = FootandMouthModel.newInstance(context)

// Creates inputs for reference.
val image = TensorImage.fromBitmap(bitmap)

// Runs model inference and gets result.
val outputs = model.process(image)
val probability = outputs.probabilityAsCategoryList

// Releases model resources if no longer used.
model.close()
```

***Figure 5 4*:** *Code for Integration of the TensorFlow Lite Model into the Kotlin*

5.3.5 System Architecture

The system architecture of the FMD surveillance prototype defines the interaction between the user interface, application logic, machine learning model, database, and reporting services. The architecture was designed to ensure that the application can operate in resource-constrained environments, with offline-first capabilities and lightweight computation using TensorFlow Lite**.** The first architectural design of the prototype was drawn on a piece of paper before translating it into executable program using Kotlin and XML to design the user interface for the application.

The architecture follows a layered design**,** consisting of the following main layers:

Machine Learning Layer (AI Model)

This is the intelligence core of the system. A convolutional neural network (CNN) trained on cattle images was integrated into the application using TensorFlow Lite**.** Its functions include: Running on-device inference to classify images, Ensuring quick response time and Minimizing reliance on cloud servers, making the app usable offline.

Presentation Layer (User Interface)

This layer allows farmers and traders to interact with the system. It was developed using Android Studio (Java/Kotlin) to provide a simple and intuitive interface. Key functions included: Capturing or uploading cattle images and Viewing real-time disease detection results.

Application Layer (Business Logic)

This layer manages communication between the user interface and the machine learning model. It handles: Image preprocessing (resizing, normalization, noise reduction) and coordinating requests for image analysis.

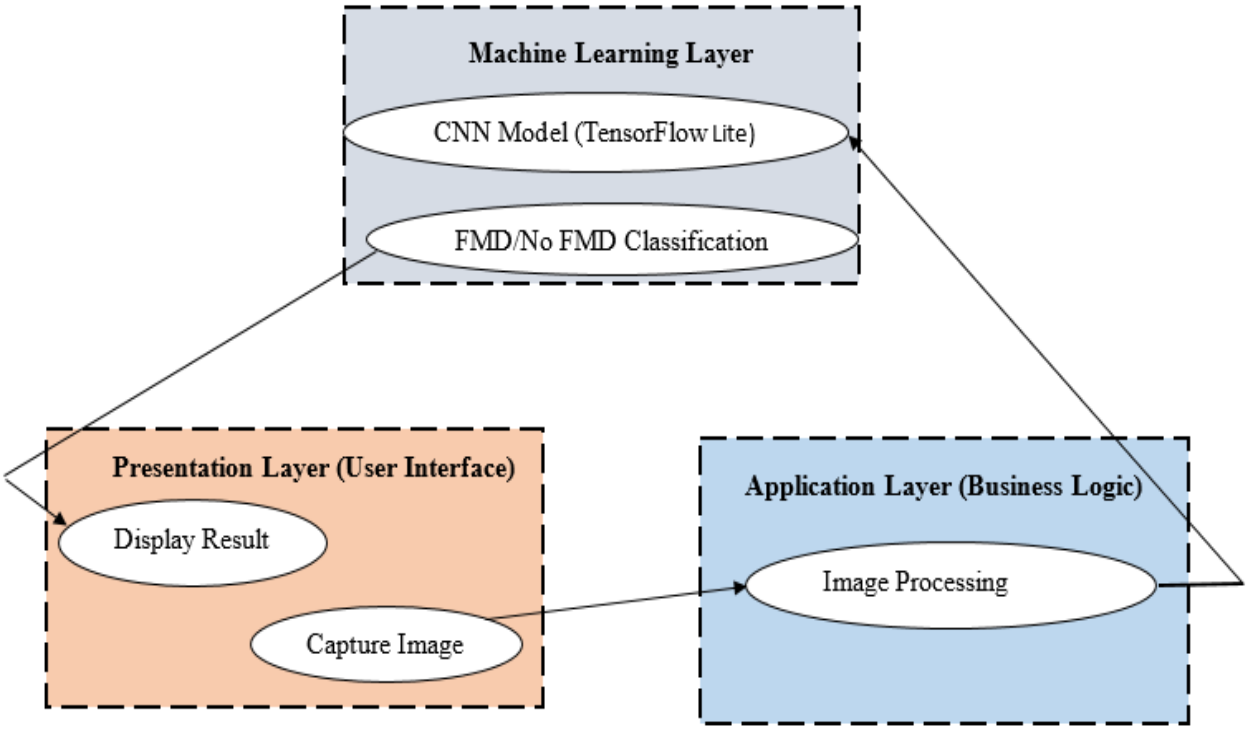


Figure 5 5: *Architecture of the prototype*

5.4 Functional Modules of the Prototype

The prototype was developed with four key functional modules, each designed to handle a specific aspect of the surveillance process. These modules ensure that users (farmers, traders, and Local Leader) can capture data, receive diagnostic feedback, and participate in disease monitoring effectively.

Image Acquisition Module

This module allows users (farmers and traders) to capture or upload images of cattle suspected of having FMD. This Module, grant access to smartphone camera to take a real-time photo and upload existing images from the gallery.

Image Processing Module

Once an image is captured or uploaded, it is automatically processed before being analyzed by the machine learning model. Preprocess images (resizing, cropping, and normalization), Improve image clarity and Convert image into a format readable by the AI classifier.

Image Classification Module

This module integrates the machine learning model trained to detect FMD symptoms. It runs locally on the device using TensorFlow Lite. It detect FMD lesions on the cattle's mouth, feet, or udder, and provide a binary classification: "FMD Detected" or "No FMD Detected."

Feedback Module

This module delivers results to the user. Display diagnostic results instantly on the user's screen.

5.5 Prototype Functionality

The process by which the mobile-based surveillance application identifies Foot and Mouth Disease (FMD) in cattle integrates computer vision, artificial intelligence, and mobile technology within a unified diagnostic workflow. The detection system is built on a Convolutional Neural Network (CNN) architecture deployed through TensorFlow Lite for on-device analysis. The identification process follows five systematic stages, as outlined below:

Stage 1: Image Capture and Upload

End users mainly cattle farmers, traders, and local leaders use the mobile application to capture or upload images of suspected cattle. The images focus on anatomical regions where FMD symptoms are most prominent, including: The mouth and tongue, to capture vesicular lesions, blisters, and excessive drooling. The feet and hooves, to identify erosions, ulcers, or inflammation. The teats,

especially in lactating cattle, to observe characteristic vesicular lesions. Captured images are stored locally within the device before undergoing automated analysis.

Stage 2: Image Preprocessing

Once the image is uploaded, the system initiates preprocessing to standardize image quality and prepare it for CNN classification. The preprocessing steps include: Resizing each image to a uniform pixel dimension compatible with the CNN input layer. Normalization of brightness and contrast to ensure consistent feature detection under varying lighting conditions. Feature enhancement using digital filters to sharpen lesion edges and textures for improved visibility. This automated preprocessing ensures that all images meet the quality threshold required for reliable classification.

Stage 3: Image Classification Using CNN Algorithm

The processed image is passed through the Convolutional Neural Network (CNN) model trained on 2,000 labeled images of cattle 1,000 exhibiting FMD symptoms and 1,000 classified as normal. The CNN extracts relevant visual features such as: Color intensity (indicating inflammation or redness), Texture irregularities (blisters, erosions, and rough surfaces), and Shape patterns (lesion contours typical of FMD infection). Based on the learned patterns, the CNN computes a prediction probability for each image and classifies it into one of two categories: “FMD-Positive” if the visual features correspond to known FMD symptoms; or **“**Normal” if no disease indicators are detected.

Stage 4: On-Device Inference and Output Display

The trained CNN model was converted into a TensorFlow Lite (TFLite) format to enable inference directly on Android devices without requiring an internet connection. Once the analysis is complete,

the system instantly displays one of the following diagnostic outcomes: *"The animal was classified Sick as it shows possible signs of FMD."* OR *"The animal was classified Normal as it shows no possible signs of FMD."*

Stage 5: Data Logging and Notification

All classified results are stored locally in the application and can be synchronized with external databases when connectivity becomes available. The app also generates notifications for potential FMD-positive cases, which can be forwarded to veterinary officers or district surveillance authorities for prompt verification and intervention.

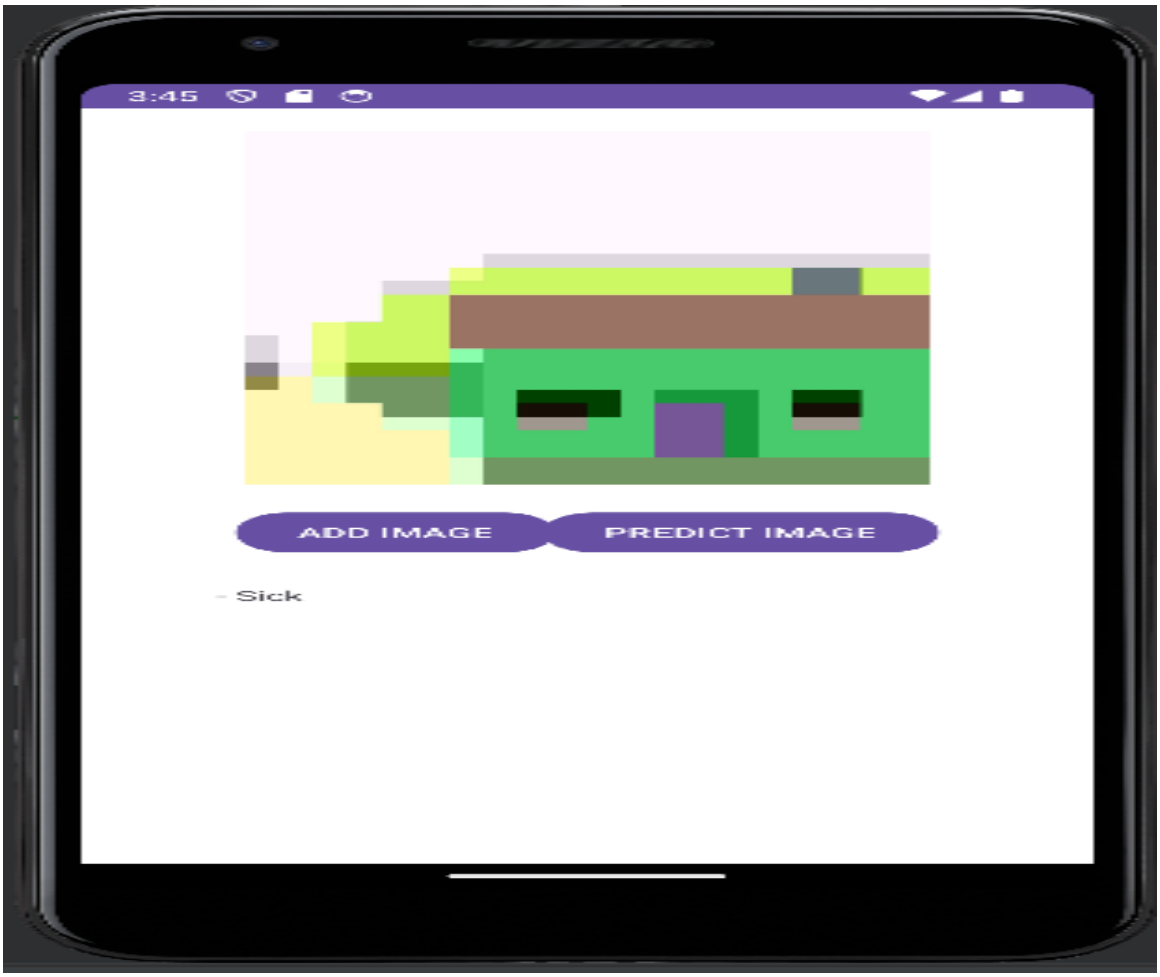


Figure 5 6**:** *A working prototype*

5.6 The Interface for Mobile App

The prototype's main interfaces are:

Image View: This displays the image uploaded by the user.

Add image button: This uploads images from the phone memory to the image view to be classified.

Predict image button: This triggers the image classification process in the background.

The text view area: This will display the output of the model either Normal to indicate that the cattle image does not have foot and mouth infection or sick to indicate that the cattle image have foot and mouth disease infection.

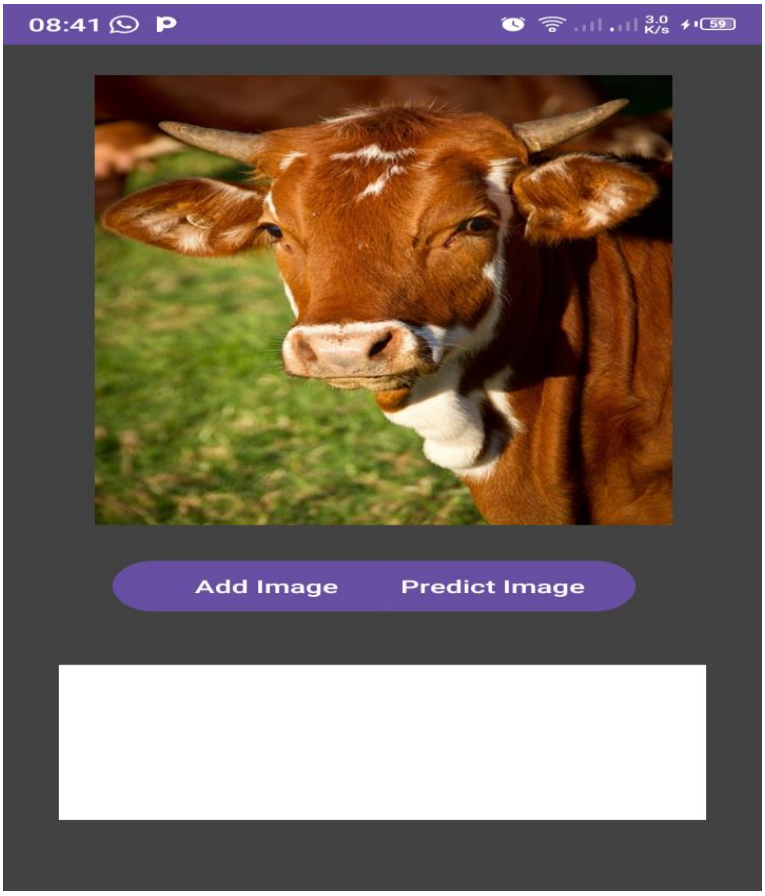


Figure 5 7: *User Interface Screen of the FMD Surveillance App.*

5.6 Prototype Evaluation

The prototype was evaluated to determine its accuracy, usability, performance, and adoption potential among stakeholders. Evaluation was conducted with a sample of 46 respondents in Koch Ongako Sub-County, including farmers and cattle traders. Feedback was collected through hands-on trials, questionnaires, and observation.

5.6.1 Usability

Usability testing focused on how easily end-users could interact with the mobile application. Quantitative analysis seen in **Figure 4.4** demonstrated that 78% of participants (36 out of 46) reported favorable usability scores, attributing their assessment to the application's streamlined functionality and focused feature set.

5.6.2 Performance

The prototype demonstrated classification accuracy of 91% compared to the bench mark of 92% with a detection time of 44 seconds as seen in **Table 4.4.** This performance metric indicates robust diagnostic capability, particularly notable given the model's optimization for mobile deployment. The statistical significance of these results supports the model's potential application in real-world veterinary surveillance systems.

5.6.3 Adoption Willingness

User acceptance testing revealed 86% of respondents expressed readiness to adopt the system for routine use. Usage patterns indicate primary application in small-scale agricultural operations rather than large-scale enterprises. Qualitative feedback demonstrated strong positive reception regarding system usability and implementation potential.

5.7 Limitations of the Study

Although the Foot and Mouth Disease (FMD) surveillance prototype demonstrated high accuracy, usability, and adoption potential, several limitations were identified during development and testing. The limitation of the Study included:

Limited Image Dataset**.** The CNN model was trained and tested using approximately 2,000 images. While adequate for prototype validation, this dataset may not fully represent all variations of FMD symptoms across different breeds, age groups, and environmental conditions.

Inconsistent Image Quality. Some images captured in field conditions were affected by poor lighting, motion blur, or incorrect focus, reducing classification accuracy in certain cases.

Restricted Study Area. The study was limited to Koch Ongako Sub-County. Broader testing across multiple regions would provide stronger evidence of the system's reliability under diverse conditions.

Device and Hardware Constraints. The app was developed and tested using mid-range Android smartphones with 16 MP cameras. Devices with lower specifications may experience reduced image clarity or slower inference performance.

Network and Data Synchronization Limitations. While the app performs on-device image classification, real-time data upload and synchronization with external databases require internet connectivity, which was unreliable in some rural areas.

Model Generalization and False Predictions. The CNN model, though accurate, may occasionally misclassify visually similar conditions. This suggests a need for continued dataset expansion and model retraining to improve robustness.

CHAPTER SIX: DISCUSSION, CONCLUSION AND RECOMMENDATION

6.1 Introduction

This chapter discusses the key findings of the study in relation to the research objectives. It also presents conclusions derived from the results, highlights the contributions of the study, and provides recommendations for practice, policy, and future research.

6.2 Discussion of Findings

6.2.1 Model's Performance and Comparative Analysis

The mobile-based Foot and Mouth Disease (FMD) surveillance system developed in this study demonstrated both functional efficiency and diagnostic reliability in detecting visible FMD symptoms among cattle. The prototype integrated a lightweight Convolutional Neural Network (CNN) model built and optimized in TensorFlow Lite, enabling real-time, on-device image analysis. The model achieved an overall diagnostic accuracy of 91 %, with a precision of 0.89**,** recall of 0.92**,** and an F1-score of 0.90**,** confirming balanced classification performance between healthy and infected cattle images. The average inference time was 2.3 seconds per image**,** validating its suitability for use in field environments with limited network connectivity.

Technically, the application comprised four primary modules: Image Acquisition Module**:** Which allows users to capture or upload images of suspected cattle lesions. Pre-processing Module**:** That standardizes image size and enhances features for optimal model input. Machine Learning Inference

Engine**:** Executes TensorFlow Lite model for on-device classification. Notification and Reporting Module**:** Displays results and records reports for follow-up.

6.2.3 Comparison with Existing Literature/Systems

The FMD surveillance prototype developed in this study shares similarities with, but also differs significantly from, existing literatures and digital surveillance systems such as **AfyaData**, **Google Trends**, and **ProMED-mail**.

Hadi et al. (2024) employed You Only Look Once (YOLO) algorithms for FMD detection, focusing exclusively on oral cavity imagery. Their dataset comprised both FMD-positive and control samples. In contrast, this study utilized TensorFlow Lite algorithms with a more comprehensive anatomical approach, incorporating imagery of feet, udder, and oral cavity regions.

Ummah (2019) investigated machine learning approaches for FMD outbreak prediction in Uganda, achieving 87.4% accuracy using Random Forest Boosting (RFB) methodology. While their research focused on environmental parameter correlation with disease patterns, this study emphasizes direct symptomatic detection through image classification.

AfyaData. AfyaData is a community-based surveillance tool that allows field workers and community members to report zoonotic and human diseases using smartphones (Karimuribo et al., 2017). Similar to AfyaData, FMD prototype emphasizes community participation in disease monitoring. Both tools utilize smartphones to empower non-experts in reporting potential outbreaks. However, while AfyaData relies primarily on manual reporting of symptoms by users, the FMD prototype introduces an AI-driven diagnostic component that automatically analyzes images to detect FMD lesions. This innovation reduces the dependency on human interpretation and provides faster, standardized results.

Google Trends. Google Trends has been widely used for digital disease surveillance by monitoring search engine queries as proxies for disease outbreaks (Carneiro and Mylonakis, 2009). While this approach offers insights into public health events, it is less effective in rural livestock settings where internet searches are rare. Compared to Google Trends, the FMD prototype directly engages livestock keepers at the grassroots level and generates primary diagnostic data rather than relying on indirect signals.

ProMED-mail. ProMED-mail is an internet-based reporting system that aggregates and disseminates reports of emerging infectious diseases globally (Madoff and Woodall, 2005). It functions as a global alert network, relying on expert inputs and official reports. In contrast, the FMD prototype is a local, farmer-centered tool that focuses specifically on cattle disease detection. While ProMED-mail plays a critical role in global early warning, it does not provide farmers with immediate diagnostic feedback.

6.2.4 Stakeholder Awareness and Adoption Potential

The study revealed that 86% of respondents were willing to adopt the mobile-based surveillance system. This high adoption potential reflects the growing trust in ICT for agriculture, consistent with Qiang et al. (2012)**,** who argued that mobile phones significantly enhance agricultural productivity and decision-making.

The strong willingness of veterinary officers to use the reporting feature aligns with Catley et al. (2012)**,** who stressed the role of participatory surveillance in improving early warning systems for animal diseases. However, challenges such as limited internet and power supply confirm the infrastructural constraints described by Sife et al. (2010)**,** who found that rural ICT adoption often faces systemic barriers.

6.2.5 Prototype Evaluation and Limitations

Evaluation confirmed that 78% of users found the prototype easy to use, appreciating features such as color-coded results. Similar usability findings were reported by Higgins et al. (2017)**,** who showed that simplicity and visual cues increase ICT adoption in low-literacy populations.

However, limitations such as model interpretability, resource constraint and variability in image quality are consistent with studies by Makau et al. (2018)**,** who noted that digital health applications in rural Africa often struggle with infrastructural weaknesses. The limited disease coverage (currently only FMD) reflects a gap also highlighted in Masuda et al. (2019)**,** who called for multipurpose livestock health platforms rather than single-disease tools.

6.3 Conclusions

This study set out to design, develop, and evaluate a mobile-based Foot and Mouth Disease (FMD) surveillance prototype for rural livestock keepers in Koch Ongako Sub-County, Uganda. The conclusions are presented in line with the specific research objectives.

6.3.1 Fulfillment of the Research Objectives

Objective One. *To investigate the state-of-the-art surveillance systems for Foot and Mouth Disease (FMD) in cattle to identify existing capabilities and operational gaps.*

The study found that about 64.4 % of farmers and traders owned smartphones with 60% of them knowing how to use it efficiently, which indicates strong technological readiness**.** Though 29% reported challenges with advanced features such as image uploading

Objective two. *To develop a machine learning model for detecting FMD symptomatology in cattle based on the capabilities and gaps identified in objective (i).*

The prototype achieved a classification accuracy of 91% and an average processing speed of 2.3 seconds per image. These results demonstrate the feasibility of deploying lightweight AI models on low-cost smartphones for near real-time disease detection in resource-constrained environments.

Objective three. *To evaluate the proposed system's performance through stakeholder engagement and validation protocols.*

The majority of respondents (86%) expressed willingness to adopt the system, showing that participatory surveillance is both acceptable and valued by the community. Farmers recognized the potential to minimize losses through early detection, traders valued transparency in livestock transactions

6.4 Contributions of the Research

The successful development of the FMD classification mobile application is expected to yield several important outcomes as discussed below:

Practical Contribution: The FMD detection prototype developed in this study empowers farmers and traders with real-time diagnostic capability by enabling the early prediction of FMD outbreaks before widespread transmission occurs. Early detection allows for the timely implementation of quarantine measures, thereby mitigating the economic and logistical challenges associated with FMD outbreaks. Furthermore, government agencies and veterinary services can adopt and scale this technology for nationwide implementation, improving overall FMD management and surveillance. By deploying the application across multiple farms, authorities can track and control disease outbreaks more effectively, reducing their impact on the livestock sector

Knowledge/Scientific Contribution: This study significantly contributes to scientific literature and the body of knowledge by offering a conceptual solution for FMD surveillance and management

by demonstrating the feasibility of deploying TensorFlow Lite AI models on low-cost smartphones for livestock disease management. Furthermore, it demonstrates how farmers, buyers, and sellers, as key stakeholders, can be actively integrated into disease surveillance. Additionally, the creative design and evaluation of the prototype using current machine learning metrics contribute to advancements in design science research.

Policy Contribution: The study provides evidence that mobile surveillance can strengthen existing veterinary services and improve livestock health systems.

Community Contribution: Finally, this study offers a participatory platform where farmers, traders, and veterinary officers collaborate in disease monitoring.

6.5 Recommendations

6.5.1 Recommendations to Practice

i) Farmers should acquire Android smartphones and familiarize themselves with their use. They should also check for regular updates of the application from the Google Play Store to ensure optimal functionality.

ii) Veterinary professionals can integrate the model into their systems so that automated SMS alerts are sent to them in the event of a suspected outbreak. This allows them to conduct laboratory confirmation and initiate disease control measures where necessary.

iii) Technology providers should consider the hardware and software requirements for model development. Additionally, more training data should be collected and integrated to enhance the model's performance.

iv) Feature enhancement should include integration with other applications to improve accessibility and interoperability.

v) Training and user support should be provided to farmers to help them download, install, and use the application effectively.

6.5.2 Policy Recommendations

The Ministry of Agriculture, Animal Industry and Fisheries (MAAIF) should support scaling of mobile-based surveillance tools by integrating them into national animal health systems.

Investment in rural internet connectivity and solar power solutions should be prioritized to overcome infrastructural barriers.

Policymakers should promote multi-disease digital surveillance platforms**,** moving beyond FMD to cover other economically important livestock diseases.

6.6 Future Work

While the prototype achieved promising results, further research is recommended to:

i) Extend the diagnostic model to include multiple cattle diseases beyond FMD.
ii) Improve image preprocessing techniques to handle low-quality images in poor lighting conditions.
iii) Optimize the prototype for older smartphones with limited processing power.
iv) Conduct large-scale field trials across different districts to validate scalability and robustness.
v) Explore integration with GIS and national veterinary databases to enhance real-time disease mapping and outbreak response.

6.7 Overall Conclusion

The development of a mobile application for FMD classification represents a significant advancement in veterinary medicine and agricultural technology. By leveraging the capabilities of machine learning and mobile computing, the application provides an innovative approach to FMD detection and management. Ultimately, this solution has the potential to enhance disease surveillance, improve animal health outcomes, and strengthen the resilience of the livestock industry against infectious disease outbreaks. The study concludes that mobile-based surveillance systems, supported by lightweight AI, are a feasible and promising approach to strengthening livestock disease monitoring in rural Uganda. The prototype successfully demonstrates how participatory surveillance, coupled with modern technology, can enhance early detection and reporting of FMD.

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7.2 APPENDICES

Appendix A: Introductory and Approval Letters

GULU UNIVERSITY

P. O. Box 166
Gulu - Uganda

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FAX +256 471 432094
Email: fs@gu.ac.ug
URL: www.gu.ac.ug

FACULTY OF SCIENCE

29th April 2021

Koch Ongako Local Leaders,
Omoro District,
Omoro - Uganda.

Dear Sir/Madam,

RE: SUPPORT FOR MR. OCEN CHARLES OLYAAKOOL (18/U /2492/MID) DATA COLLECTT0N

Cordial greetings from the Faculty of Science, Gulu University!

I write to introduce to you **Mr, Ocen Charles Olyaakool,** who is a second year student at Gulu University pursuing a Master's of Science in Information and Communications Technology for Development. He is currently conducting a study on Mobile Phone Based Surveillance of Foot and Mouth Disease in Cattle.

With this letter, therefore, I kindly request you to provide **Mr, Ocen Charles Olyaakool** with the necessary assistance on data collection in your District/Sub County. His data collection tool has been approved by the Gulu University Research Ethics Committee.

Looking forward to your support in this request as together we can contribute to better monitoring of Livestock diseases and well-being of this nation.

Yours faithfully,

GULU UNIVERSITY
29 APR 2021
DEAN
FACULTY OF SCIENCE

Benedict Oyo (PhD)
Dean, Faculty of Science
Email: b.oyo@gu.ac.ug

GULU UNIVERSITY

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RESEARCH ETHICS COMMITTEE

23/04/2021

To: Ocen Charles

Gulu University

0779224854

Type: Initial Review

Re: GUREC-2020-30: Mobile Phone-Based Surveillance for Foot and Mouth Infectious Disease in Cattle, Version 2.0, 2021-04-21

I am pleased to inform you that at the **72nd** convened meeting on **18/02/2021**, the Gulu University REC, committee meeting, etc voted to approve the above referenced application. Approval of the research is for the period of **23/04/2021** to **23/04/2022.**

As Principal Investigator of the research, you are responsible for fulfilling the following requirements of approval:

1. All co-investigators must be kept informed of the status of the research.

2. Changes, amendments, and addenda to the protocol or the consent form must be submitted to the REC for rereview and approval **prior** to the activation of the changes.
3. Reports of unanticipated problems involving risks to participants or any new information which could change the risk benefit: ratio must be submitted to the REC.
4. Only approved consent forms are to be used in the enrollment of participants. All consent forms signed by participants and/or witnesses should be retained on file. The REC may conduct audits of all study records, and consent documentation may be part of such audits.
5. Continuing review application must be submitted to the REC **eight weeks** prior to the expiration date of **23/04/2022** in order to continue the study beyond the approved period. Failure to submit a continuing review application in a timely fashion may result in suspension or termination of the study.
6. The REC application number assigned to the research should be cited in any correspondence with the REC of record.
7. You are required to register the research protocol with the Uganda National Council for Science and Technology (UNCST) for final clearance to undertake the study in Uganda.

The following is the list of all documents approved in this application by Gulu University REC:

No.	Document Title	Language	Version Number	Version Date
1	Protocol	English	Version 2.0	2021-04-21
2	Data collection tools	English and Luo	Version 2.0	2021-04-21
3	Informed Consent forms	English and Luo	Version 2.0	2021-04-21
4	GUREC COVID 19 Measures	English	One	2020-12-19

Yours Sincerely



Dr. Gerald OBAI

For: Gulu University REC

GULU UNIVERSITY, FACULTY OF SCIENCE, DEPARTMENT OF COMPUTER SCIENCE

14/06/2021

TO:

Office of Chief Administrative Officer, Omoro District.

Permision granted for him to collect academic research data from Ongako sub-county.

THRU:

Office of District Veterinary Officer, Omoro District

For CHIEF ADMINISTRATIVE OFFICER OMORO DISTRICT

17/06/2021

Dear Sir/Madam

Re: Recommendation for Research Data Collection in Koch Ongako Sub County.

Am a final year Student of Gulu University offering Master of Science in Information and Communication Technology. I'm currently conducting my study on Mobile Phone Based Surveillance of Foot and Mouth Disease in Cattle.

It is in this light that I request your Office through the Office of District Veterinary Officer to offer me a recommendation letter to allow me carry out research data collection in the Koch Ongako Sub County.

Attached is a copy of approval letter from Gulu University Ethical Review Committee, Introductory letter from Faculty of Science, Participants' Consent form and Data Collection Tool.

Looking forward to your usual support as together we can contribute to better monitoring of Livestock diseases and well-being of this Nation.

Yours' faithfully,

Ocen Charles Olyaakool,
Sign:.....
Tel: 0779224854
Email: charlesocen@gmail.com

Appendix B: Consent Documents/Forms (English and Luo Versions)

Version 2.0

C) Consent Form

Title of Study:

Mobile Phone-based Surveillance of Foot and Mouth Diseases in Cattle.

Researcher/Investigator:

Name: Mr. Ocen Charles Olyaakool

Course: Master of Information and Communication Technology (ICT4D).

Department: Computer Science, Gulu University.

Phone: 0779224854

Email: charlesocen@gmail.com

Purpose of the Study:

Your invitation to partake in this research is as a result of my feeling that your experiences has a significant contribution towards our understanding as well as knowledge of foot and mouth disease. It is important that you understand why this research is being conducted and what it involves. Please read then information carefully and you are open to discuss this with anyone you feel comfortable, have your time for reflection and decide whether you intend to take part in this research or not.

The purpose of this study is to find out how the residents of Koch Ongako is monitoring or checking on FMD and how they report cases of FMD as well as presence of any specific system for FMD surveillance. There after I intend to develop a mobile phone app for the surveillance of Foot and Mouth Disease in cattle.

Study Procedures:

You as a cattle Keeper, Buyer and Local Leader in Koch Ongako shall be availed with the consent form in English and Luo version out of which, you chose the version you are comfortable with. Upon consenting, you shall then be given the questionnaires to fill out also both in English and Luo version.

GULU UNIVERSITY
INSTITUTIONAL REVIEW COMMITTEE
APPROVED UNTIL
★ 23 APR 2022 ★
FACULTY OF MEDICINE
P. O. Box 166, Gulu

You contribution in this research process will be as an individual and shall take about 10 to 20 minutes for interview questionnaire.

Risks:

The foreseeable risks during this is that since we are in the era of Covid 19, exchange of research materials and interactions of the researcher with participants may lead to spread of Covid 19. Secondly, sick animals may be encountered during the study. However, there should be no cause for alarm as Putting on Face masks, washing hands with sanitizers and social distancing shall strictly be observed during this study to minimize the spread of Covid 19 and the sick animal(s) should be isolated.

Benefits of the study:

The information that shall obtained during this study will help the participants and the community at large to beware of FMD and possible ways of monitoring and reporting.

Confidentiality:

Your responses during this study will be anonymous and you are not supposed to write your name or any identifying information on the questionnaire. All your filled questionnaires shall be tightly locked in the researcher's personal cabinet and participants' data shall be kept confidential unless the researcher is legally obligated to share it. In case of violation of rights or abuse, a participant can report to Gulu University Ethical Review Committee (GUREC) who is the guarantor of this study.

Compensation:

There shall be no compensation for your time when participating in this research process. Your participation in this research process is voluntary and it is entirely your decision to partake or no. If you accepted to participate, you will be asked to sign the consent form and you may still be free to withdraw from this study even after signing the consent form.

Contact:

Should you have any questions/enquires any time during this research process or should you experience any effects as a result of participating in this research, please contact the researcher on his contacts on the first page of this form. In case of questions about violation of rights or abuse, contact Gulu University Ethical Review Committee (GUREC) on +256 471432096/+256 772305621 or email to

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INSTITUTIONAL REVIEW COMMITTEE
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★ 23 APR 2022 ★
FACULTY OF MEDICINE
P. O. Box 166, Gulu

[redacted].

Consent:

I have read/it has been read to me and I understand the information provided. I had the opportunity to ask questions and have been responded to. I fully understand that my participation is voluntary and am free to withdraw any time I wish without offering a reason and without cost. I understand that I shall be given a copy of this consent form. I hereby agree to participate in this research study.

Participant's Signature..... Thumb Print [ ] **Date.....**

Witness's Name:.....Signature..... Thumb Print [ ] **Date...**

Investigator's Signature..... Date.....

GULU UNIVERSITY
INSTITUTIONAL REVIEW COMMITTEE
APPROVED UNTIL
★ 23 APR 2022 ★
FACULTY OF MEDICINE
P. O. Box 166, Gulu

C) Waraga me moko tam.

Wii lok me Kwed:

Tic ki diro me cim me nyino cok cok two dog ki obong tyen dyang

Lakwed:

Nyinga: Mr. Ocen Charles Olyaakool

Kwan Ne. Master of Information and Communication Technology (ICT4D).

Dul Me Pwonye: Computer Science, Gulu University.

Namba Cim: 0779224854

Email: charlesocen@gmail.com

Kwed eni tye mi ngo?:

Lwongi me mino tam mi i kwed man tye lube ki tam ma ni ngec ma itye kwede romo konyo wan nyang ma ber i kom two obong tyen dyang. Pire tek ni omyero i nyang pi ngo kwed man ki tye timo ne. A legi ni i kwan lok man ma ber, dok i romo leyo ne kin gat mo ma i twero, ci i mok tam mi.

Kwed man tye me nyang ngo ma dano me Koch Ongako tiyo kwede me ngino ki roto two obong tyen dyang, ki ka gwok diro mo tye me ngino ki roto two obong tyen dyang. I yo ngeye, a mito yupu diro me cim ma romo ngino ki roto two obong tyen dyang.

Kit ma Kwed bi wot kwede:

In ma calo lagwok dyang, lawil onyo latela te dero ki bi mini waraga me moko tam mi ma ki coyo i leb Munu ki Acholi. I bi yero ma i mito ne, I pongo ci ki mini waraga me lepeny. Mino tam mi i kwed man bi bedo ma calo in, dok bi tero dakika 10 nio 20.



Peko ma twero nen i kara me kwed man:

Kit ma calo kari man me two Korona ni, gwe nye ki waraga mogo i kin dano romo medo nya pa two man. Me aryo, lee mogo ma kum dong lit ki romo nongo gi. Kadi bed ku meno, pa mo ma pol myero obed pee li weny pi en ki bi ruku face mask, lwoko cing ki sanitizers ki bedo ma kin dano boo, bi konyo dwoko rwom me nya pa two korona. Lee mogo ma kum gi lit ki bi gwoko gi ka ken gi..

Ka ber pa kwed man:

Lok onyo nyec ma ki bi nongo ki I kwed man bi konyo lu mi tam wa ki lwak duci me nyang ma tut i kom two obong tyen ki yo ma ki twero ngino ki roto twoman.

Gwoko Mung:

La gam mi i lok kum kwed man bi bedo i mung dok omyero pe i co nyingi i kum waraga me lapeny ma ki bi mini. La gam wu ducu ma ocoyo i waraga man ki loro wiye i bok pa la kwed lok nio wang ma cik mo tye ma mito ni ki mi loki woko. Ka gwok ki turu twero ni i kare me kwed man, go repot bot Gulu University Ethical Review Committee (GUREC) ma gin aye gu ye ni kwed man otim me.

Cul onyo Oteny dud:

Cul mo bi bedo pee pi cawa ni ma i dyero pi kwed man. Mino tam mi i kwed man dic mo pee i yee. Ka i yee me mino tam mi i kwed man, ci ki bi leg gi me keto cingi i waraga man me moko ni i tye atera me mino tami. i romo bene pud weko mino tam mi kadi ka onongo dong i keto cingo woko i waraga man.

Yoo me Kub be:

Ka i tye ki lapeny mo keken I kare me kwed man onyo I tye ka nongo adwogi mo keken ma luke ki mino tam mi I kwed man, Bed a gonya me kub be ki la kwed man in numba cim ma tye I pot karatac me acel ni. Ka gwok nyo I mito penyo lapeny ma lube ki turu twero ma megi, ci kub be ki Gulu University Ethical Review Committee (GUREC) I numba cim +256 471432096/+256 772305621 onyo cwali gi waraga ki intanet I email gurec@gu.ac.ug.

Acwako:

A kwano ongo ki kwan na waraga man ci anyang lok ma tye. Abedo ki kare me penyo peny ci lagam me bene ki mina. Anyang ma ber ni mino tam ma dic mo pee iye, dok atye agonya me weko ne woko

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labongo tito pi ngo ne. Anyang bene ni ki bi mina bwut waraga man me moko tam ni. An dong en aye me mino tam ma i lok kum kwed man.

Cigneca Pa Lami Tam..... Di Cingi ☐ **Nino Dwe.....**

Nying Caden:.....Cigneca..... Di Cingi ☐ **Nino Dwe.....**

Cigneca Pa La kwed kwed.....Nino Dwe.....

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Appendix C: GUREC COVID 19 Measures

Measures for the Prevention and control of risk of spread of COVID-19 during the implementation of research

Study Title: Mobile Phone-Based Surveillance for Foot and Mouth Infectious Disease in Cattle

Principal Investigator (s): Ocen Charles Olyaakool

Introduction:

The novel Coronavirus is transmitted from human to human through droplets and direct or close personal contact with an infected individual

Novel Coronavirus signs of infection include respiratory symptoms, fever, and cough, shortness of breath and breathing difficulties. In more severe cases, infection can cause pneumonia, severe acute respiratory syndrome, kidney failure and even death

The government of Uganda has since March 2020 issued guidelines and imposed restrictions that are intended to prevent the spread of COVID 19. Although travel restrictions have been eased, they remain in place. Further, Uganda National Council for Science & Technology (UNCST) issued guidelines to researchers/investigators on how best research can be conducted in the country in line with the ministry of Health guidelines on prevention of COVID-19 and without compromising the rights, welfare and safety for both research participants and research teams

Implementation of the prevention and control measures

In the implementation of the research activities, the investigators are committed to ensuring the safety of its research team, research participants and communities where the study will be

conducted. The study team undertakes to comply with the Standard Operating Procedures issued by the Ministry of Health, and presidential directives to mitigate against the risk of infection of COVID-19, rapidly detect and effectively respond to any COVID-19 case that may occur in the process of carrying out the study, screening, face covering, physical distancing, and good hand hygiene.

Procedures to be followed during the implementation of the research.

Prior to data collection and Training

1. **Health guidance:** There will be training sessions dedicated for COVID-19 sensitization and awareness, to equip the research team with knowledge of signs and symptoms of the COVID-19, and preventive measures such as hand hygiene before placing and removing the mask, as well as storage of the mask, social distancing. The research team will circulate notices, posters, charts on common signs and symptoms of COVID-19 as provided by the Ministry of Health, and develop and/or use existing plan for the appropriate referral pathway for identified and/or suspected cases.
2. **Personal Screening:** All researchers, research assistants, research participants and any other individuals engaged in research activities will screen temperature daily for fever. Screening for temperature will be carried out during planning meetings, trainings, community outreach. Any individual found with COVID 19 symptoms will be withdrawn and referred to the COVID – 19 task force for further assessment and management. The withdrawn individual will be allowed to return only if they present a valid certification of their COVID-19 status showing negative result
3. **Wearing face coverings:** All researchers and research assistants and any other individuals engaged in research activities that require interaction with fellow researchers or research

participants or the community member will have to wear a face mask that fully covers the mouth and nose at all times. The study will provide face masks for individuals who do not have.

4. **Physical Distancing:** There will be social distancing during the training, meetings, community outreach of at minimum of 2 metres. During breaks, the team will not be allowed to congregate in common areas.
5. **Good hygiene:** All team members will be required to wash their hands or use hand sanitizers before and after entering the training room, and other common areas. Hand washing equipment shall be supplied and made available at all times. All surfaces and equipment shall be sanitized frequently.

During data collection

1. **Personal Protective Equipment (PPE):** All research assistants involved in tracing of respondents and in in-person interviews and research participants will use PPE including a properly fitted face mask. Enumerators/Researchers and research participants will wash hands with soap and water or use hand sanitizer prior to the interview. Handshakes and hugging are prohibited. Physical distancing of at least 2 meters in all research related activities shall be observed.
2. **Focus group discussions:** The research team shall carry educational materials on prevention of COVID-19 in a language understood by the participants. These materials shall also have visual images to support understanding. Enumerators/Researchers and research participants will wash hands with soap and water or use hand sanitizer prior to the interview. Screening for temperature will be carried out prior to conducting meetings
3. **Consent Process:** The Researcher /Research assistants will observe social distancing when taking consent (while 2 meters apart) upon arrival to the participant.

Enumerators/Researchers and research participants will wash hands with soap and water or use hand sanitizer prior to the interview. Participant will then be sensitized on covid-19 and presented with preventive measures.

4. **Equipment sanitization:** shared devices used to record or capture data shall be sanitized regularly.

During Dissemination/Community engagement

1. **Community Engagement:** The research team shall carry educational materials on prevention of COVID-19 in a language understood by the participants. These materials shall also have visual images to support understanding. Enumerators/Researchers and research participants will wash hands with soap and water or use hand sanitizer prior to the interview. Screening for temperature will be carried out prior to conducting community engagements.
5. **Equipment sanitization:** shared devices used during community engagements to shall be sanitized regularly.

The preventive and control measures will continuously be reviewed based on new information and guidelines communicated by the Ministry of Health



Appendix D: Data Collection Tools/Interview Guides (Luo and English)

Version 2.0

D) Instruments

Questionnaire for Cattle Keepers, Buyers, Abattoirs operators and Local Leaders

a) Participant's Personal information

1. **Gender:**

☐ Female ☐ Male

2. **Age:** 18-30 31-53 54-76 *(Tick as appropriate)*

3 **Education Level Attained:** NONE PLE UCE UACE DIPLOMA DEGREE (Others).....

b) Questionnaire.

1. Is there any measure for monitoring/checking FMD in your area?

Yes ☐ No ☐

If Yes, Specify.....

2. Do you always report cases of FMD?

Yes ☐ No ☐

3. Through which means do you usually report FMD cases?

Phone ☐ Letter ☐

4. Do you get feedback after reporting?

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Yes ☐ No ☐

5. By which means do you get the feedback

SMS ☐ Call ☐

6. How does most people in your area get information?

Radio ☐ Phone ☐

7. Are you always provided with Information about FMD?

Yes ☐ No ☐

If Yes, How? .....

8. Does most people in your area possess smart phones?

Yes ☐ No ☐

9. Can you use a smart mobile phone efficiently?

Yes ☐ No ☐

10. Are you aware that you have role to play in surveillance of FMD?

Yes ☐ No ☐

Thank you so much for your willingness to participate

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Lapeny pi joo magi: Lugwok dyangi, Luwil dyangi, Lunek dyangi ki Lutela.

a) Lok kum ngat ma gamo lapeny

1. **An Lacoo** **An dako**

2. **Mwaka:** 18-30 31-53 54-76 *(gwet kit ma rwate kede)*

3 **Rwom kwan:** PLE UCE UACE DIPLOMA DEGREE PEE AKWANO
(gwet kit ma rwate kede)

b) Questionnaire.

1. Tye kit yo mo me ngino/roto two obong tyen dyang i ka bedo ni?

Eyo ☐ Ku ☐

Ka Eyo, Ci waci.....

2. Pol i dwoko repot pi two obong tyen dyang ka tye tim me?

Eyo ☐ Ku ☐

3. Yo mene ma pol i dwoko ki repot pi two obong tyen dyang?

Cim ☐ Waraga ☐

4.I nongo lagam mo i nge dwoko ki repot pi two obong tyen dyang?

Eyo ☐ Ku ☐

5. I yo mene ma inongo ki lagam man

SMS ☐ Call ☐

6. Pol pa dano kam ma ibedo iye ni gi nongo ngec gi ki yo ango?

Radio ☐ Cim ☐

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7. In mono pol kare ki mi ni ngec ma dok i kom two obong tyen dyang?

Eyo ☐ Ku ☐

Ka eyo, ci nining? .....

8. Pol pa dano i ka bedo ni gi tye ki cim smart?

Yes ☐ No ☐

9. I romo tic ki cim smart maber?

Eyo ☐ ☐

10. I ngeyo ti ka ni i tye ki tic atima I kum ngino two obong tyen dyang?

Eyo ☐ Ku ☐

Apwoyo ma tek me yee gamo lapeny

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