BUSITEMA UNIVERSITY
Pursuing Excellence

AN AI BASED SYSTEM THAT DETECTS MASTITIS IN DAIRY CATTLE

BY

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DECLARATION

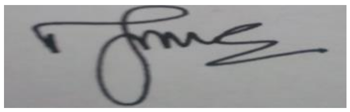
I KEMIGISHA ZANERAH BU/UG/2018/2192 declare that this project report is original and has not been published or submitted before to any university or higher institution of learning.

Sign :

Date : 22/11/2022

APPROVAL

This final year project under the title "AN AI BASED SYSTEM THAT DETECTS MASTITIS IN DAIRY CATTLE" is under my guidance and is now ready for examination.

Signature: 

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ABSTRACT

Mastitis is a common disease that prevails in cattle owing mainly to environmental pathogens; they are also the most expensive disease for cattle in dairy farms. Several prevention and treatment methods are available, although most of these options are quite expensive, especially for small farms. Uganda's dairy sector plays a vital role in household nutrition income levels. It contributes to the (GDP) of the economy. In order to help dairy farmers to control the disease is by making them aware of the disease or detect the disease early, an AI based system that detects mastitis has been developed using two datasets of 35445 datapoints got from a total of 24 dairy cows along with several of their sensory parameters (collected via inexpensive sensors) and their prevalence to mastitis. Machine learning and Deep learning approaches were deployed to determine the most effective parameters that could be utilized to predict the risk of mastitis in dairy cattle. In order to achieve this, the K-means clustering algorithm for feature engineering, Decision tree classifier and Artificial Neural Networks were used for classification of which animals were sick and those that were healthy. The system comprises three major subsystems—the mastitis detection device using a non-contact infrared temperature sensor, web application, and the dB SQLite database server. The mastitis detection device consists of an infrared temperature sensor that can detect the different udder quarter temperatures and the web application that consists of two models that is the temperature model that analyses the temperatures of the udders before milking operations and the milk model that evaluates the degree of conductivity in the milk immediately after the milking operations are carried out. Importantly, the proposed system utilizes a wireless network connection from the ESP 32 microcontroller with low power consumption that connects the information of the health of the cattle on the display device with the remote management system from the dB SQLite database server. The application can predict the risk of mastitis in dairy cattle in real time using temperature from the different udder quarters and the Electrical conductivity in milk with an accuracy of 98.5% and 89.6% respectively. Experimental results reveal that the proposed system can reduce the risk of milking cattle with mastitis and improve efficiency of milk production

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List of Acronyms

AI	Artificial Intelligence
AMS	Automatic Milking System
ANN	Artificial Neural Network
API	Application Interface
CMT	Carlifonia Mastitis Test
EC	Electrical Conductivity
GDP	Gross Domestic Product
GUI	Graphical User Interface
IC	Integrated Circuit
IDE	Integrated Development Environment
IMI	Intra-Mammary Infection
IR	Infra Red
MCMT	Modified California Mastitis Test
REST	Representational State Transfer
SCC	Somatic Cell Count
SCL	Serial Clock
SDA	Serial Data
SQL	Structured Query Language
URL	Uniform Resoure Locator
USB	Universal Serial Bus
WIFI	Wireless Fidelity

1 CHAPTER ONE: INTRODUCTION

1.1 Background

Mastitis is frequently brought on by microbial infections (mostly bacterial) from the environment, either directly or through feed, which finally result in pathological lesions and inflammation of the mammary glands and may even bring on severe toxemia in the cattle. The type of infection and the cattle's mammary gland's resistance are the key factors that define the severity of the symptoms. [1].

Mastitis is a complicated illness that manifests in both clinical and sub-clinical stages. [2]. Clinical mastitis is characterized by observable signs of udder inflammation and gross abnormalities in the quantity and quality of milk. Sub-clinical mastitis, on the other hand, continues to be a herd problem because there are no observable clinical signs or gross changes in the milk, and it can be detected by a variety of indirect tests, including the Modified California Mastitis Test (MCMT), Somatic Cell Count (TSCC), NA Gase Test, and Electrical Conducive Test [2]. Despite the fact that sub-clinical mastitis is a global problem, it continues to infect other members of the herd and result in significant financial losses to milk supply. [3].

In Uganda, subclinical mastitis is quite common, and findings suggest that the problem is made worse by ineffective therapy and antibiotic resistance. [4]. Despite the fact that these significant studies show that mastitis is becoming more common, little is known about how common clinical mastitis is in this country. Most farmers in Uganda are unaware of subclinical mastitis, despite the fact that it is economically more significant to the dairy business (due to concealed symptoms)[4], they are aware of clinical mastitis, perhaps as a result of the visible symptoms, which they view as an impending threat to cows. Additionally, clinical mastitis is extremely important since it results in both animal misery and financial loss. [5].

In addition to lowering milk production, the prevalence of mastitis places a financial burden on farmers because each clinical case of mastitis results in medical costs, veterinary costs, labor costs, premature culling losses, non-saleable milk losses, future reproductive losses, replacement losses, and or death losses. [1]; For smaller farms or those in low-income countries, the costs could be enormous. [6]. Antibiotics alone or in combination with non-steroidal anti-inflammatory drugs (NSAID) are frequently used for mastitis prevention, and they are effective in preventing the majority of economic loss caused by clinical mastitis. However, such a strategy should only be used for treatment as long-term use of such drugs for prevention rather than treatment results in antibiotics or drug residues reaching the end consumers, which results in drug or antibiotic resistance-related issues. [1].

The identification of related pathogens may be helpful in treating the condition and in helping to make wise management decisions [4]. Husbandry and management methods are crucial for the effective control of mastitis [7]. In fact, the characteristics of the pathogen responsible for the infection have a significant impact on the likelihood of cure, suggesting that pathogen identification greatly enhances mastitis treatment protocols[7]. The industry now employs some of the several mastitis measures that have been proposed [8]. Since somatic cell count (SCC) has

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