tion to inform the farmer instantly of any abnormalities. Furthermore, LED indicators and a piezo buzzer are included to provide instant local alerts to on-site farm employees, ensuring intervention even if the farmer's phone is off.

Oestrus and Disease Detection Mechanisms. The system's primary objective is the accurate and early identification of impending health crises and reproductive readiness

Early Disease Detection: Early detection is essential for maintaining herd health, reducing [2] economic losses, and minimizing the spread of contagious diseases, especially major threats in Zimbabwe like Lumpy Skin Disease (LSD), Foot and Mouth Disease (FMD), anthrax, and tick-borne diseases [2]. The system monitors continuous data points like body temperature, heart rate, and activity levels to identify deviations from the norm, allowing prompt intervention before diseases advance. For example, a temperature detected above the normal cattle body temperature triggers an alert. Detecting health issues early minimizes treatment costs [3].

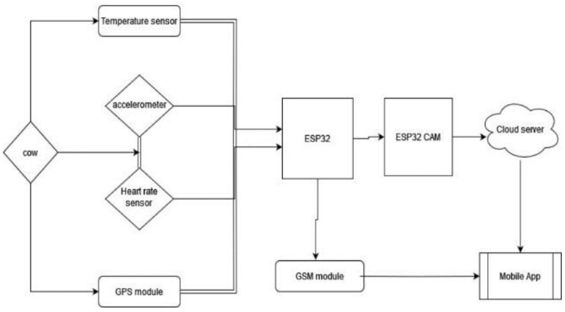

Figure 1 – System design flow chart

Oestrus Cycle Detection: Efficient reproductive management hinges on accurately detecting the oestrus cycle. This is crucial because the optimal window for successful breeding or artificial insemination lasts only 12 to 18 hours every 21 days. The system monitors changes in behavior, activity levels, and other physiological indicators to accurately predict oestrus. The system specifically aims to detect levels of excitement and movement consistent with oestrus. Using IoT-based systems for accurate detection helps to reduce costs associated with reproductive hormones and unnecessary inseminations. The system utilizes data analysis to match collected data with already-known symptoms of certain diseases or indications of oestrus cycles.

Implementation Challenges and Future Directions. The practical implementation of IoT-based monitoring systems faces notable challenges. These limitations include budget constraints and reliance on stable internet connectivity and infrastructure, particularly in remote or rural areas. Obtaining cooperation from dairy farms to provide information and statistics due to security and privacy policies can also be a limitation.

A key technical challenge encountered during prototype testing was the presence of system noise, resulting in sensor value fluctuations. This noise stemmed from integrating components manufactured by different vendors, potentially utilizing different signal processing values.

To mitigate noise and ensure accurate functioning, future development should focus on standardizing the signal processing values used by all integrated components. Architecturally, future research recommends investigating the integration of Edge-Fog-Cloud computing for precise and quick outcomes in disease prediction and reproductive cycle tracking, based on promising models in smart healthcare. Additionally, leveraging advanced data analysis techniques, specifically Machine Learning (ML), is advised for early disease identification and risk prediction in dairy herds.

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UDC 681

A REVIEW OF MODERN INTELLIGENT AND ENERGY-EFFICIENT TOBACCO CURING SYSTEM

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Abstract. The article reviews the core technological components that enable intelligent and energy-efficient control of modern tobacco curing systems. Traditional flue-curing is a highly energy-intensive process relying heavily on subjective manual control, leading to high fuel consumption and variable leaf quality. This review focuses on the integration of Machine Vision (MV), specifically Convolution Neural Networks (CNN), automated leaf recognition and Fuzzy Logic Control for precise barn parameters, that is temperature and humidity. The Specific Energy Consumption (SEC) is analysed. The paper concludes that intelligent systems offer a significant pathway to minimize operational cost ensuring uniform, high-quality cured tobacco.

Keywords: machine vision, tobacco curing, deep learning, fuzzy control, energy efficient.

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Introduction. The accuracy of curing is a major factor in the value of flue-cured tobacco. To produce the desired chemical and physical qualities of the leaf, the controlled drying process known as flue-curing is essential. The farmer's subjective evaluation of leaf colour is currently the main determinant of this procedure. This process has three distinctive stages: yellowing, colour-fixing and stem-drying.

Given that conventional wood-fired barns are renowned for their energy inefficiency, this results in uneven quality and significant energy waste. They greatly increase the cost of production and deforestation. In response, modern agriculture engineering has shifted towards intelligent and automated systems to standardize leaf quality and to critically reduce SEC. This paper reviews foundational mathematical models that underpin these intelligent, energy-efficient tobacco curing systems.

System Architecture and Methodology. The intelligent tobacco curing systems architecture has three functional layers: the Sensing and Vision layer, the Control and Processing layer and the Actuation layer.

Sensing Layer and Vision Layer. This is the layer that is responsible for gathering real-time data in the environment.

Environmental Sensors: Digital temperature and humidity sensors (dry-bulb and wet-bulb) are strategically placed around the curing chamber to monitor air conditions, that is the temperature and humidity.

Machine Vision Module: A low-cost camera is installed in the barn to capture high-resolution images of the tobacco leaves. These images of the tobacco leaves are processed on an Edge Computing device (Raspberry Pi or ESP32-CAM module) to minimize latency.

Deep Learning Module: A custom-trained Convolution Neural Network (CNN) is installed on the edge device. This installed model is trained on a dataset of images. The dataset of images is captured under actual bulk curing barn conditions to classify the leaves into distinct stages. The stages are yellowing, browning and drying degrees. This classification replaces the subjective human eye observation.

The success of the image recognition model, is critical for real-time process control.

Control and Processing Layer. The fundamental of the intelligence of the system is in the control system. The objective is to adjust the environmental setpoints (temperature and relative humidity) in the barn based on the output of the Machine Vision module.

Fuzzy Logic Control (FLC): A fuzzy logic controller is implemented on a microcontroller. FLC is ideal because the curing process inherently involves precise, linguistic and experiential rules for example "If leaf is mostly yellow and humidity is too low, then slightly increase the humidity setpoint".

Input Variables for FLC: current curing stage (from MV module), current temperature and current relative humidity.

Output Variables for FLC: The outputs are control signals sent to actuation layer such as Heater Duty Cycle Adjustment and Ventilation Damper Angle.

The controller identifies the curing stage by colour and environmental parameters and adjusts temperature, humidity and ventilation to prevent color defects, thereby improving quality and market value of the cured tobacco.

Actuation Layer. This layer has electromechanical system that executes the controller's commands to maintain the optimal curing environment.

Heater/Blower System: An electrically controlled heat source and a conventional fan are used to circulate and adjust and control the temperature of the air in the barn.

Automated Dampers/Vents: Stepper motors or servo-actuators automatically adjusts the fresh air intake and exhaust vents. Controlling these vents is important so as to prevent over ventilation which can waste significant heat during the final curing stages.

Energy Efficiency and Sustainability

Fuel Reduction. By precisely matching the heat and ventilation to the leaf's actual requirements, the FLC minimizes heat loss, which is particularly relevant given that traditional barns can lose up to 98.5 % of supplied energy. Continuous systems like tunnels can reduce coal consumption from 3–4 kg to 0.7 kg per kg of dry tobacco. The automated FLC system is expected to this efficiency even higher in small-to-medium scale bulk curers.

Conclusion. The evolution of tobacco curing from an art to a science is driven by the successful combination of Machine Vision (CNNs) for real-time quality assessment and Fuzzy Logic for adaptive human-like but precise control will improve product quality while promoting long-term environmental sustainability.

A significant measurable reduction in the fuel-to-tobacco ratio is realized compared to manually-operated conventional barns, directly addressing the national challenge of deforestation.

Acknowledgments.

I am grateful for the insightful guidance of my supervisor, Mr Didymus T. Makusha. I thank the Harare Institute of Technology (HIT) and the Belarusian National Technical University (BNTU) for co-organizing this conference and providing a platform for this research.

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UDC 681

IMPLEMENTATION OF ROBOTICS IN IMPROVING SAFETY AND EFFICIENCY IN MINING OPERATIONS

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Abstract. Mining operations present hazardous conditions, particularly in post-blast environments where the accumulation of toxic gases poses significant risks to worker safety. This study presents a robotic system designed to autonomously navigate underground mining terrains and detect harmful gases such as methane, carbon monoxide, and carbon dioxide. The robot is built with a rocker-bogie mechanism for stability on uneven surfaces and uses IR sensors for obstacle detection. Gas detection is carried out using a sensor-integrated circuit. A GSM module is used to transmit the gas concentration data to surface-level receivers. Simulation results confirmed the robot's capability to navigate autonomously and detect gas presence with reliable accuracy.

Keywords: Autonomous Robot, Gas detection, Underground Mining, GSM communication.

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Introduction. Underground mining remains one of the most hazardous industrial activities, especially in the post-blasting phase, where the presence of toxic gases poses serious risks to worker safety and operational efficiency. Commonly encountered gases such as methane (CH_4), carbon monoxide (CO), and carbon dioxide (CO_2) are not only dangerous due to their toxicity but also because they are difficult to detect without specialised equipment (Bakshi, 2021). The traditional practice of manually inspecting mine shafts and tunnels after blasting exposes workers to unnecessary risks, delays in decision-making, and reduces productivity. As mining operations increase in scale and complexity, there is a growing demand for intelligent, automated systems that can navigate hazardous environments and gather essential environmental data without human intervention (Patel, 2023).

This paper focuses on the design and development of a robotic system tailored for underground mining applications. The system integrates three core technologies: a rocker-bogie mobility mechanism, a gas detection circuit, and a wireless GSM communication module. The rocker-bogie system was selected due to its proven ability to traverse uneven terrain Ahmad (2022). It ensures that the robot maintains ground contact with all wheels, improving stability and traction in debris-laden or rugged underground surfaces. For autonomous navigation, the Probabilistic Roadmap (PRM) algorithm was implemented in MATLAB to simulate safe path planning in a cluttered environment.

Methodology. The methodology adopted for this project focuses on the design, simulation, and integration of key subsystems that enable the mining robot to operate autonomously in hazardous underground environments. These include the mechanical mobility system, the path planning algorithm, gas sensing circuitry, GSM-based communication, and embedded programming The robot's chassis was developed using a rocker-bogie suspension system.

Figure 1 – Rocker-bogie mechanism

To enable autonomous navigation, the Probabilistic Roadmap (PRM) algorithm was implemented in MATLAB. The environment was modelled with obstacle maps representing underground tunnels. The output was a smooth, collision-free path that the robot could follow. The algorithm's effectiveness was visualised through simulated maps that displayed node generation, obstacle inflation, and final path selection.

The robot's sensing system included three key sensos MQ-4 for methane, MQ-7 for carbon monoxide and MG-811 for carbon dioxide. These sensors were integrated into a circuit designed in Proteus software. Each sensor's analogue output was connected to the Arduino Mega microcontroller for real-time gas concentration reading. Voltage dividers and signal conditioning circuits were included to stabilise readings and reduce noise interference.

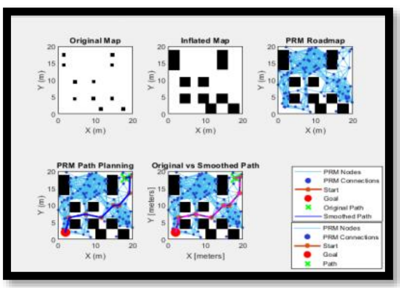

Figure 2 – PRM path planning simulation results