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AIoT-Driven Edge Computing for Rural Small-Scale Poultry Farming: Smart Environmental Monitoring and Anomaly Detection for Enhanced Productivity

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Abstract—Smart environmental monitoring and corrective measures in small-scale poultry farming leads to significant improvements in productivity. The growing demand for chicken production has emphasized the importance of maintaining optimal conditions to improve quality and productivity.The integration of Artificial Intelligence (AI) and the Internet of Things(IoT) is recommended for the efficient management of the farm's environment. A potential solution is presented in this paper, utilizing IoT-based sensor nodes with ARM Cortex M3 - LPC 1769 and LORA technology to monitor chicken farms across diverse regions.The proposed solution incorporates a low-cost edge computing server-Jetson Nano device equipped with a machine learning model to categorize and monitor live environmental conditions in poultry farms. Real-time data from various branches is collected and analyzed using machine learning classification techniques including logistic regression, K nearest neighbors, and support vector machines.The performance of these algorithms is compared to identify the most effective approach. Upon evaluation, the K nearest neighbors emerges as the superior performer, achieving an impressive accuracy of 99.72% and an execution duration of 0.087 seconds on the Jetson Nano edge computing device. This cost-effective technology is tailored for small businesses in regions where farmers can gain valuable insights from data-driven decisions and closely monitor their operations. By incorporating AIoT into farm management, the challenges faced by small-scale poultry farming can be addressed, empowering farmers with enlightened techniques to improve overall productivity and quality.

Keywords-Artificial Intelligence,Internet of Things, Poultry farm Monitoring, Edge computing

I. INTRODUCTION

The introduction of standardized farming methods and enhanced manufacturing procedures has led to significant growth in the worldwide chicken production industry over the past few decades. The demand for high-quality chicken food has risen due to increasing consumer awareness about the safety of chicken products [1]. Chicken is recognized as the most popular form of meat consumed globally, owing to its abundance of nutrients, including high-quality protein, low fat, and low cholesterol [1].However, the production of gases such as ammonia (NH_3) and hydrogen sulfide (H_2S), which emit foul odors, remains a primary environmental concern in poultry farms. Dust generated from feed mill operations and the storage and processing of solid waste, such as manure, dead birds, and hatchery waste, all contribute to these odor issues. Furthermore, water usage for cleaning tasks can exacerbate these problems, and the presence of rats and flies introduces additional difficulties [2].

Poultry farms employ various strategies to address these issues. Precautions include maintaining adequate ventilation and air flow to control odors from off-gas emissions, as well as using dust-removal equipment in feed factories to improve the working environment [3]. Effective management of solid waste involves procedures such as composting, routine manure collection, and proper disposal of deceased birds. To limit environmental impact, it is crucial to find efficient ways to handle reproductive waste, including eggshells, unhatched eggs, and liquid waste. These techniques could include methods like open burning or the use of imaging equipment. In general, by implementing suitable mitigation measures and adhering to ethical waste management practices, the environmental consequences associated with chicken farm operations can be reduced.

Traditional poultry farming is often characterized by manual management methods, which may not sufficiently preserve the health and growth of chicks [4][5]. The introduction of automated systems for running chicken farms is necessary, particularly due to labor shortages. The suggested approach aims to significantly enhance the administration and oversight of chicken farms by incorporating automated methods. The proposed solution offers an innovative approach to address the challenges faced by poultry farmers,

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emphasizing cost-effectiveness, asset-saving, quality-oriented, and productive management of chicken farming. Furthermore, it provides a convenient and efficient way of monitoring and managing poultry farms for small-scale industries through the utilization of AIoT (Artificial Intelligence of Things) technology.

II. LITERATURE SURVEY

Li, N et al. [6] conducted a survey and highlighted the significance of monitoring poultry behavior for both animal welfare and Precision Livestock Farming (PLF). The study revealed that behavior served as a non-invasive indicator of welfare, contributing to enhanced poultry health and production quality. Modern technologies, such as sound analysis and wireless wearable sensors, enabled continuous monitoring and real-time tracking of individual birds. Moreover, image processing technology provided direct measurements of behavior and early disease warning. Despite the promise shown by these technologies for commercial applications, their implementation faced certain challenges. Advancements in PLF systems were deemed necessary to improve data processing and device detection for commercial validation. The potential benefits of fully developed PLF systems included enhanced animal welfare, health, and overall efficiency for poultry farmers.Chigwada et al. [7] proposed a low-cost IoT-based remote poultry management system designed for small to medium-scale farmers. The system effectively monitored and regulated various parameters such as temperature, humidity, water level, ammonia gas, and lighting. This implementation resulted in reduced labor costs, time savings, and improved egg production, mainly due to unique light scheduling. The system provided remote accessibility through a web portal, enhancing convenience for farmers.The implementation of this innovative system has the potential to support multiple United Nations Sustainable Development Goals (UNSDGs), including ending poverty and achieving zero hunger. Policy support was considered essential for addressing food security challenges in the context of poultry farming. Additionally, research on poultry technology and disease detection was identified as a means to enhance resilience and support the achievement of UNSDGs in developing countries.

Lufyagila et al. [8] discussed the significance of poultry health for growth and production. The challenges faced by Tanzanian smallholder farmers in adopting automated systems due to cost constraints were addressed. In the past, an IoT-based system was developed, offering a cost-effective solution for monitoring poultry conditions and resulting in time and cost savings. The implementation of such systems has the potential to empower smallholder farmers and improve poultry health and productivity in Tanzania.Singh et al. [9] conducted a comprehensive evaluation of chicken health monitoring using artificial intelligence (AI) methods on an internet of things (IoT) platform. The research explored IoT device tracking using sensors, video/image processing, and audio-based poultry analysis. Considering the importance of eggs and poultry as main sources of protein and the availability of cheap computer resources and common methods, there is a compelling case for using modern technology to continuously monitor large farms and increase production. In poultry farming, especially in small-scale industries in rural areas, the application of AIoT offers significant benefits with cost-effective and user-friendly solutions. This empowers smallholder farmers, addresses poultry management challenges, and contributes to sustainable agriculture and improved livelihoods in rural communities. However, existing systems still face limitations in terms of accuracy and execution time. To overcome these challenges, the proposed system aims to monitor multiple poultry barns and classify environmental conditions with low cost, high performance, and high speed. By incorporating AIoT technology, this system seeks to revolutionize poultry farming practices, ensuring efficient and accurate monitoring of poultry house conditions for enhanced productivity and welfare.

III. PROPOSED SYSTEM

The proposed system comprises two modules: the Poultry Farm Environment Monitoring and Management (PFEM) IoT node and the Artificial Internet of Things (AIoT) edge server module. The system overview is depicted in Figure 1. Each poultry farm is monitored using the PFEM IoT node, which incorporates various environmental monitoring sensors. The temperature is regulated by controlling the fans. Data from the PFEM IoT nodes of different branches is transmitted to the Thing Speak cloud via the LORA module. The AIoT edge server, equipped with a JETSON Nano computing device, utilizes machine learning algorithms and data from the cloud to monitor the environmental parameters of various poultry farm branches. It classifies whether the poultry farm environment is normal or abnormal for chicken growth.

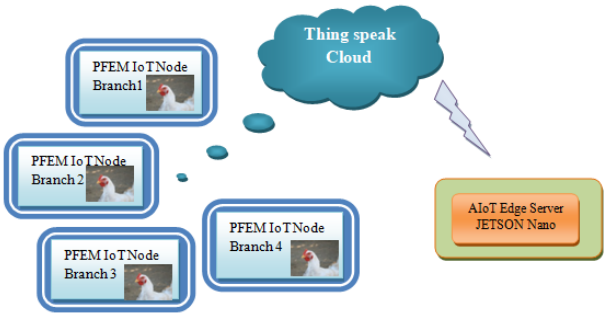

Fig.1.AIoT- Poultry Farm monitoring system architecture

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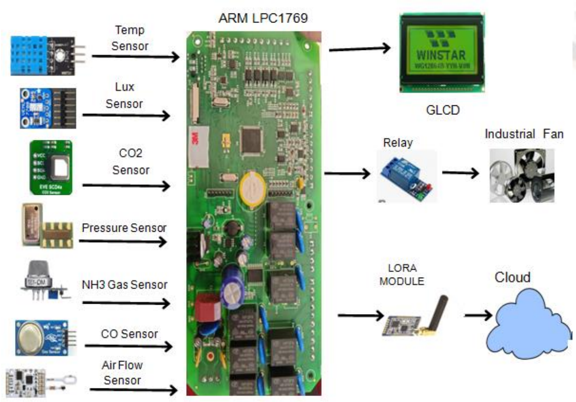
IV. PFEM IOT NODE

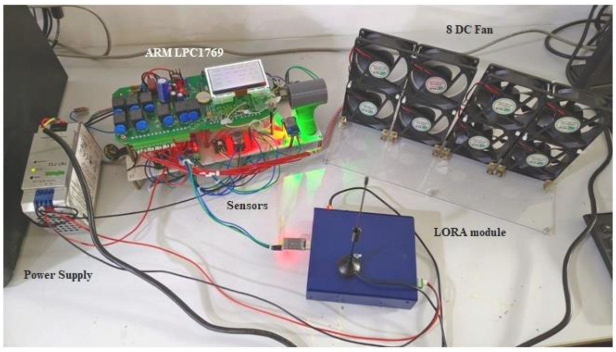
PFEM IoT node is designed to monitor the environment of poultry farm and regulate the temperature of farm using industrial fan. The main processing unit is ARM CORTEX M3 LPC 1769. [10]The ARM Cortex M3 - LPC 1769 is a feature-rich microcontroller with a 32-bit RISC architecture, clock speed up to 120 MHz, 512 KB flash memory, multiple communication interfaces, low power consumption, built-in ADC and DAC, and high-speed GPIO pins. Figure 2a represents the various sensors interfaced with LPC 1769 and Fan controlled through relay. Figure 2b is hardware implementation of PFEM IoT node.

The poultry farm monitoring system incorporates various sensors to ensure accurate and efficient data collection. The HTU31D temperature and humidity sensor offer precise readings with fast response times, making it ideal for monitoring environmental conditions. The VEML7700-TT lux sensor measures ambient light levels, providing valuable insights into the lighting system's effectiveness. For gas monitoring, the SCD4X CO2 sensor covers a wide output range and operates with low power consumption, while the MQ 137 ammonia gas sensor and MQ 7 CO sensor offer high sensitivity to NH3 and carbon monoxide, respectively.

These sensors are essential to detect potential threats and protect the welfare of poultry. A wind sensor based on a hot-wire anemometer is used to monitor airflow; it provides accurate data with hardware control of ambient temperature. DC fans are also integrated into the system, which ensure energy-efficient and adjustable air flow to maintain ideal conditions in the hen house. [11][12]The poultry farm parameters and their corresponding desired values include maintaining a temperature of 27°C or lower, maintaining humidity levels between 40% and 70%, ensuring carbon dioxide (CO2) levels remain below 2500 ppm, keeping ammonia levels below 25 ppm, and providing light intensity within the range of 20 to 50 lux.



a. Architecture of PFEM IoT Node



b. Hardware Implementation of PFEM IoT Node

Fig. 2. PFEM IoT Node of Poultry farm

The SX1262-LoRa-DTU is a reliable wireless transmitter for sending data wirelessly over long distances. It employs LoRa technology to reduce interference. Its multilayer relay network and AES encryption enable secure and effective data transfer, making it appropriate for many protocols and industries. Only these sensors and wireless technologies enable a complete and sophisticated poultry farm monitoring system.

The pseudo code for the PFEM IoT node is depicted in Figure 3. Sensors measure temperature, humidity, pressure, CO2, CO, NH3, light, and airflow every 5 seconds. Values are transmitted to the controller using I2C protocols, then calibrated and sent to the cloud via the LORA module. The system controls fans based on temperature: 2 fans are activated at 27°C-29°C, 4 fans at 29°C-33°C, and all 8 fans above 33°C. Additionally, if the temperature remains constant for one minute, the fan rotation sequence is initiated, optimizing usage and power consumption.

Pseudo code of PFEM node

```
Assume Temperature=T, Humidity=H, carbon-di- oxide=CO2,
carbonmonoxide=CO, Ammonia=NH3,
Pressure=P,Airflow-A,LuX-L,LPC1769-µC,DC
fan=DCF1,DCF2,DCF3,DCF4,DCF5,DCF6,DCF7,DCF8
while(1)
{
  for every 5 sec:
    T, H, CO2, CO, NH3, A, LP ➔ µC
     µC ➔ LORA module ➔ Thing speak cloud
     µC ➔GLCD display
if T <27°C constant
          DCF1 to DCF8 = off
else if T=27°C to 29°C
         DCF1, DCF2=ON
else if T=29°C to 33°C
        DCF1-DCF4=ON
else if T>33°C
        DCF1-DCF8=ON
}
```

Fig. 3. Pseudo code for the PFEM IoT node

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V. IOT CLOUD

The sensor data from the PFEM IoT nodes in the poultry farm branches is transmitted in real-time to the ThingSpeak cloud platform. ThingSpeak is an IoT platform that collects, visualizes, and analyzes data in the cloud[13][22]. It supports a variety of embedded devices and assigns unique channel IDs.

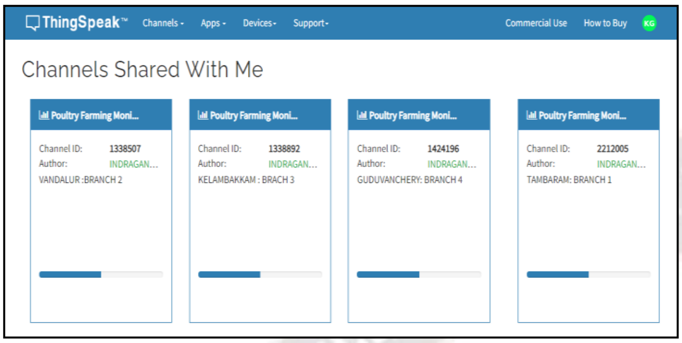

Fig. 4. Thing Speak IoT dashboard of Poultry Farm

Fig. 5. Live visualization of Poultry farm of branch 1

Each channel is associated with a specific PFEM IoT node through an API key. This enables the visualization of up to eight different parameters in the cloud. Only authorized individuals can access the Thing Speak cloud, where they can monitor the live data and take actions based on specific values.

Figure 4 represents IoT cloud dashboard of four Poultry farm branch with unique channel IDs. By selecting a specific channel, real-time sensor values can be viewed as a graph, providing a live visual representation of the data as shown in figure 5.

VI. ARTIFICIAL INTERNET OF THINGS (AIOT) EDGE SERVER MODULE

The AIoT edge server module is implemented using the Jetson Nano embedded edge computing platform, running Ubuntu 18.04 Linux operating system. With the USB Dual Band WiFi Network Card featuring the RTL8811CU chip and USB 2.0 interface, seamless integration with the Jetson Nano is achieved. This integration empowers the Jetson Nano to establish wireless connections, utilizing both the 2.4GHz and 5GHz frequency bands.

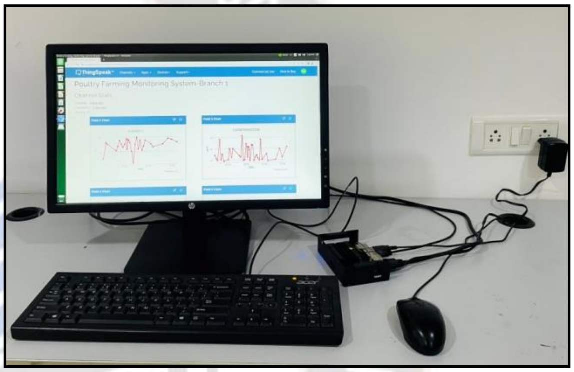

Fig. 6. AIoT Edge computing server-Jetson Nano

Consequently, the network card significantly enhances the Jetson Nano's networking capabilities, facilitating reliable and efficient WiFi connectivity. The figure 6 shows the hardware implementation of AIoT edge computing server.

VII. EDGE AI MODEL DEVELOPMENT

The AIoT edge computing server is utilized for remote monitoring of environmental parameters across multiple branches. It also employs a machine learning model to classify the condition of specific poultry farms as normal or abnormal. Figure 7 illustrates the workflow of the AI model on the Jetson Nano. The PFEM IoT node comprises device integration, data acquisition, and data storage blocks. Device integration involves connecting environmental monitoring sensors to the processing unit and LoRa module. In our proposed system, eight parameters, namely temperature, humidity, pressure,CO2, NH3, CO, Airflow, and light conditions, are collected from the poultry farm using the data acquisition unit. The PFEM IoT node then transmits the calibrated values to the data storage unit, specifically the Thing Speak cloud.

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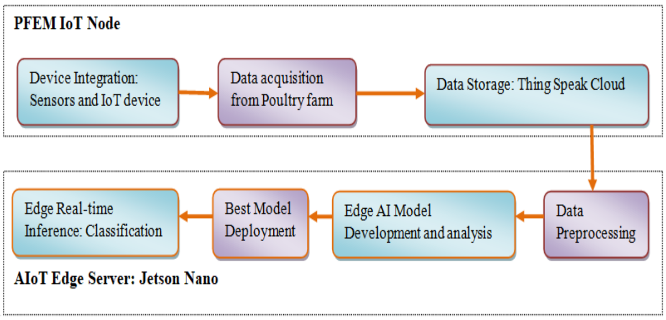

Fig. 7. Workflow of AI model in Jetson nano

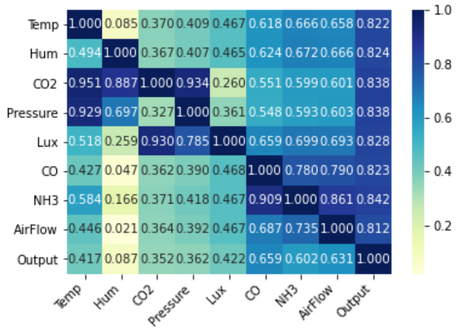

Fig. 8. Predictive Power Score of poultry farm dataset

The AIoT edge Jetson Nano system receives real-time data from four branches via the cloud. The dataset is generated by utilizing cloud data and includes information about both normal and abnormal environmental conditions in a poultry farm, based on sensor values. The dataset consists of eight independent features and one dependent feature, which indicates whether the poultry farm environmental condition is normal or abnormal.

A. Data Preprocessing

AIoT preprocessing is converting unstructured IoT data into a format that can be used by machine learning AI models. The method includes a number of crucial steps. First, data cleaning removes errors and discrepancies to allow for precise analysis. The next step is feature selection or extraction, which increases prediction accuracy by locating valuable attributes. For thorough analysis, data integration compiles data from several IoT sources into a single dataset. The goal of outlier identification is to locate and control anomalies that could skew results. Resampling and regulating erratic time-series patterns are necessary when handling time-series data. Unbiased analysis is ensured by scaling features through normalization or standardization. For effective model training, data augmentation produces new data. Filtering out interference and sensor mistakes is a part of noise reduction.

The dataset is prepared for model testing, validation, and training by data splitting. The Predictive Power Score (PPS) [14] is a versatile metric that can identify relationships between variables, regardless of their data types. It is an asymmetric measure that can capture both linear and non-linear dependencies. The score ranges from 0, indicating no predictive power, to 1, representing a perfect predictive relationship. Figure 8 represents the heatmap of PPS scores between the variables of poultry farm data set, with higher scores indicated by warmer colors.

In the development of the Edge AI model, three supervised machine learning algorithms, namely Logistic Regression (LR), K-nearest neighbors (KNN), and support vector machine (SVM) classification, are employed. The performance metrics of these algorithms are carefully analyzed, and the best-performing model is selected for deployment on the Jetson Nano edge computing device. To ensure accurate evaluation and assessment of the model, the dataset is split into training and testing subsets. The training dataset is utilized to develop the machine learning model, while the test dataset is used to evaluate its performance. In the suggested approach, the dataset is split so that 40% of the data is utilized to assess the model's performance, while 60% of the data is set aside for model training. This method offers a thorough examination of the model's capacity to generalize to new data and produce accurate predictions

B. Logistic regression

A logistic function is used to represent the dependent variable in the machine learning classification technique known as logistic regression [14][15]. The logistic function is commonly referred to as the sigmoid function and is a mathematical operation that converts an input real number into a probability value between 0 and 1.

$$Logit(P) = b_0 + b_1 I_1 + b_2 I_2 + b_3 I_3 .. + b_k I_{k1} \qquad (1)$$

Logistic regression is to construct a best fit model that predicts the likelihood of obtaining one of two possible results indicating whether the environment on a poultry farm is normal or abnormal based on input variables. Once the best fit model is formulated, the coefficients' values can be accessed within the provided equation 1, wherein 'p' signifies the probability of obtaining binary results and I_1, I_2, I_3……I_k are independent features[16]. In the proposed system k value is 8.

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C. KNN classification algorithm

K Nearest Neighbors (KNN) is a machine learning approach that can be used for classification and regression tasks. Its functionality involves recognizing the k nearest neighbors from the training dataset that are closest to a new unknown data and then predicting the label of the new unknown data. [17] [16]Euclidean distance metric is used to find the distance between new data and trained data. Consider A as the input data and B as the trained data. In this context, the Euclidean distance(Ed) between these two sets is quantified by the equation (2).

$$Ed(A,B) = \sqrt{\sum_{n=0}^{i} (\ A_n - B_n)^2} \quad (2)$$

The KNN algorithm is non-parametric in nature. It is a versatile and powerful machine learning method that can be applied to a wide range of problems. The value of k is a hyperparameter that the programmer must set. The accuracy of the KNN algorithm is influenced by the value of k [17]. A lower k number makes the algorithm more precise, but it also makes the method more susceptible to noise. On the other hand, a higher k number makes the algorithm more resistant to noise, but it may also lead to reduced accuracy.

D. Support Vector Machine classification algorithm

Support vector machines (SVMs) [20, 21] are a supervised learning technique that can be used for both classification and regression tasks. They are an effective machine learning approach and are commonly employed in various fields, such as fraud detection, text classification, and image classification. Even if the data points are not linearly separable in the original feature space, SVMs can still find a hyper plane that separates the data points of two different classes by transforming the original feature space into a higher-dimensional space using a kernel. SVMs can use different kernels depending on the problem to transform the data into a higher dimensional space. Equation 3 gives the SVM decision function f(x), Where N is the support vectors, α_i is co-efficient, b is bias term and k is the kernel function with support vector xi and unknown data x. Table 1 shows SVM kernel function formulas.

$$f(x) = \sum_{i=1}^{N} \alpha_i \ y_i \, k(x_i, x) + b \quad (3)$$

TABLE I. SVM KERNEL FUNCTIONS

Kernel function	**Mathematical formula**
Linear	$k(x_i, x) = x_i^T . x$
Polynomial	$k(x_i, x) = (x_i^T . x + c)^d$; c=constant, d=degree
Radial Basis Function	$k(x_i, x) = \exp^{-\left(\frac{\|x_i - x\|^2}{2\sigma^2}\right)}$; σ=width of Gaussian
Sigmoid	$k(x_i, x) = \tanh(\alpha x_i^T x + c)$; α = c = constants

Linear kernels transform data points to a higher-dimensional space where they are linearly separable. Polynomial kernels map data points into a higher-dimensional space where they can be separated by a curved hyperplane.RBF (Radial Basis Function) kernels map the data points into a higher-dimensional space where they are separated by a spherical hyperplane. Sigmoid kernels map data points into a higher-dimensional space where they are separated by a sigmoid hyperplane.

VIII.ANALYSIS OF PERFORMANCE METRICS

Evaluation metrics play a crucial role in assessing the performance of AI machine learning models. The performance metrics of an AI model for classification are accuracy, precision, specificity, recall, and F1 score. Accuracy represents the ratio of correctly predicted instances to all predictions made. Precision evaluates the proportion of predicted positive instances that were genuinely positive, while specificity measures the ratio of accurately predicted negative instances among all negative predictions. Recall calculates the fraction of actual positive instances that were correctly identified as positive. To strike a balance between precision and recall, the F1 score comes into play. It combines both metrics into a single accuracy measure. Although accuracy provides a useful overall performance indicator, it may be misleading when dealing with imbalanced class distributions. In such cases, precision and recall offer more insightful evaluations, particularly for specific classes. Hence, the F1 score serves as a valuable compromise, capturing the interplay between precision and recall to provide a more comprehensive assessment of the model's performance [23].

Equations 4, 5, 6, 7, and 8 present the formulas for computing various performance metrics in classification tasks, namely accuracy, precision, specificity, recall, and F1 score [24]. These metrics are represented using True negative (T_N), False negative (F_N), False positive (F_P), and True positive (T_P) values. These equations allow us to quantitatively evaluate the model's performance by comparing the correctly classified instances with the misclassifications for different evaluation criteria.

$$\text{Accuracy} = \frac{(T_P + T_N)}{(T_P + T_N + F_P + F_N)} \quad (4)$$

$$\text{Precision} = \frac{T_P}{(T_P + F_P)} \quad (5)$$

$$\text{Specificity} = \frac{T_N}{(T_N + F_P)} \quad (6)$$

$$\text{Recall} = \frac{T_P}{(T_P + F_N)} \quad (7)$$

$$\text{F1 score} = 2 * \frac{(\text{Precision} * \text{Recall})}{(\text{Precision} + \text{Recall})} \quad (8)$$

The Figure 9 presents the performance of the KNN algorithm for various K values on the Jetson Nano. Figure 12 illustrates the comparison of AI models based on their execution times.

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The accuracy remains consistently high, ranging from 99.55% to 99.72%. Notably, K=3 to K=6 achieve a perfect precision of 100% while K=7 to K=9 maintain a commendable 99.36%. The specificity, indicating the accurate identification of negative instances, is 100% for K=3 to K=6 and 99.77% for K=7 to K=9. The recall, reflecting the ability to identify positive instances, remains at 98.95% for all K values. The F1 score, balancing precision and recall, ranges from 99.15% to 99.47%. Moreover, the execution time for KNN predictions is generally low, varying from 0.087 to 0.099 seconds. Considering these results, K=3 to K=6 are optimal choices, particularly if precision and specificity are critical. For quicker execution, K=3 stands out as the most suitable option.

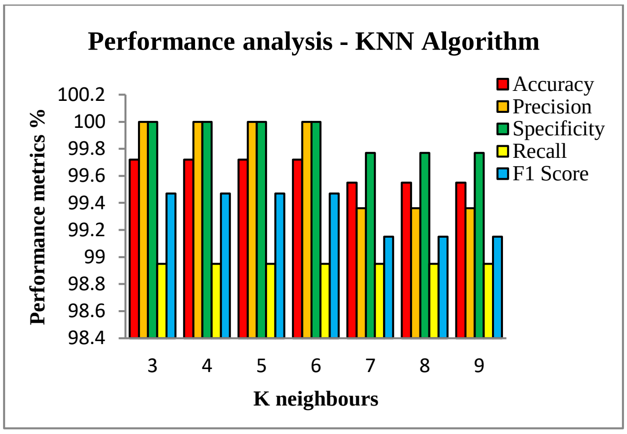

Fig.9. Performance analysis of KNN algorithm.

The figure 10 presents the performance of SVM with different kernels on the Jetson Nano. All kernels achieve high accuracy, ranging from 95.50% to 99.83%. The linear kernel stands out with perfect precision of 100%, indicating all positive predictions are correct. For recall, the polynomial and RBF kernels achieve 100%, effectively identifying all positive instances. In terms of execution time, the linear kernel is the fastest, taking only 0.173 seconds, while the sigmoid kernel is slower at 0.692 seconds.

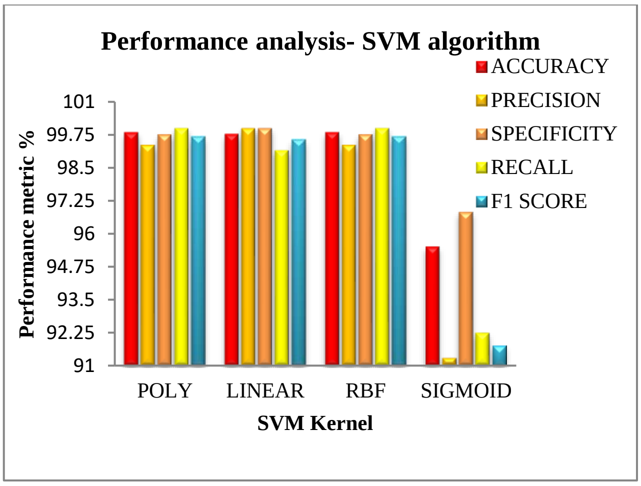

Fig.10. Performance analysis of SVM algorithm

considering the trade-off between accuracy and speed, the linear kernel appears to be the most attractive option for applications on the Jetson Nano, providing a good balance between these key performance metrics.

The Logistic Regression model on the Jetson Nano shows impressive performance with high accuracy 99.66% and perfect precision and specificity 100%, indicating correct classification of positive and negative instances. It achieves a commendable recall of 98.74%, effectively capturing most positive instances. The F1 score of 99.36% reflects a good balance between precision and recall is shown in figure 11. Moreover, the model's execution time is low, taking only 0.134 seconds, making it efficient for real-time or resource-constrained applications.

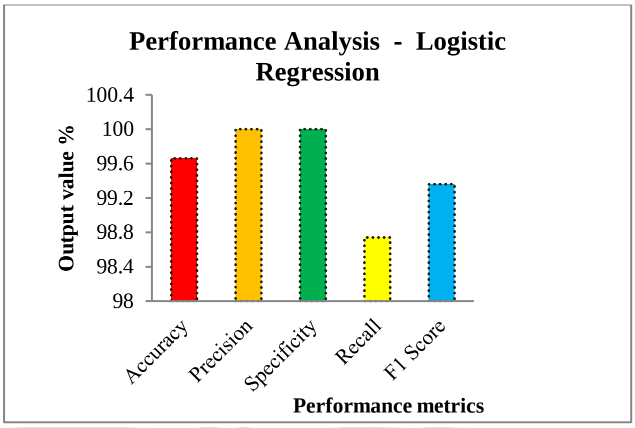

Fig. 11. Performance analysis of Logistic Regression algorithm

Figure 12 showcases the efficiency of each model in terms of processing speed. Considering the importance of quick data analysis, the figure allows us to identify the most time-efficient AI model for the given application. Execution time is a crucial factor to consider, especially for real-time applications and resource-constrained devices like the Jetson Nano. In the context of poultry farm environment monitoring, where prompt decision-making and responsiveness are essential, minimizing the execution time is of paramount importance. Among the AI models evaluated, KNN exhibits commendable execution times, with K=3 and K=4 achieving the lowest time of 0.087 seconds. This indicates that KNN can process and classify data quickly, making it suitable for real-time monitoring in a poultry farm environment. While the execution times for KNN increase slightly for higher K values, the differences remain relatively small. Considering the emphasis on execution time, KNN with an appropriate K value, such as K=3 or K=4, emerges as an optimal choice for poultry farm environment monitoring on the Jetson Nano. Its efficient execution time ensures timely data analysis and decision-making, making it a practical and responsive solution for monitoring the farm conditions effectively. The AI model,

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utilizing the K-Nearest Neighbors algorithm, has been deployed on the Jetson Nano, creating a real-time interface for an AIoT based edge computing system.

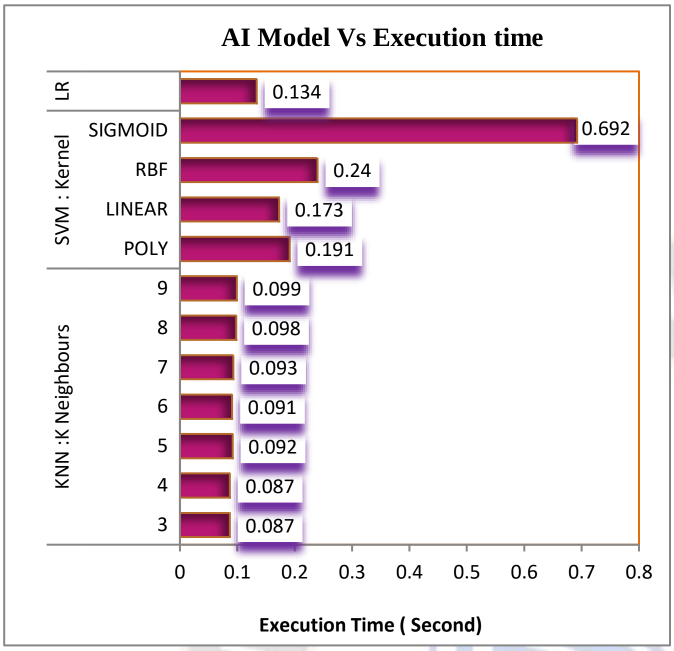

Fig. 12. Comparison of AI model with execution time

This system is designed to monitor and classify the environmental conditions in various branches of a small-scale poultry farm as either normal or abnormal. By leveraging the Jetson Nano's processing capabilities and the efficiency of the KNN algorithm, the AIoT system can swiftly analyze incoming data, allowing timely detection of any anomalies or irregularities in the poultry farm environment. This proactive monitoring approach aims to enhance the overall management and productivity of the small-scale poultry industry, ensuring optimal conditions for poultry health and sustainable operations.

IX. CONCLUSION

The proposed AIoT- based edge computing system for small-scale poultry farm monitoring is a cost-effective and environmentally friendly solution. The system utilizes efficient processing capabilities and the KNN algorithm to achieve real-time monitoring and data analysis at a relatively low price point. This is especially beneficial for small-scale industries with limited budgets, enabling them to access advanced AI capabilities without significant financial investments. Additionally, the system's proactive monitoring approach helps ensure a better environment for the poultry farm by promptly detecting and addressing any anomalies or irregularities in the environmental conditions. This timely intervention leads to improved poultry health, increased productivity, and enhanced overall farm management. By integrating AIoT and edge computing technologies, small-scale poultry farms can create a more sustainable and efficient environment, optimizing resources and minimizing environmental impact. Overall, the AIoT-based edge computing system for small-scale poultry farm monitoring is a promising technology with the potential to revolutionize poultry farm management. Its cost-effectiveness, environmental friendliness, and proactive monitoring capabilities make it an attractive option for small-scale industries seeking to improve their operations.

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