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Ammonia Detection and Prediction in a Poultry Farm using Machine Learning

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Abstract— **The concentration of ammonia within poultry sheds is a constant risk to flock health, productivity, and profitability, but most farms only make the occasional manual measurement that does little to provide a predictive sense. We created a low-cost monitoring platform that integrates Internet of Things (IoT) sensing and machine-learning analytics to enable real-time, predictive ammonia management. The sensing layer consists of two ESP32 microcontrollers: each controller combines an MQ-135 gas sensor (for ammonia) with a BME280 sensor that measures temperature, humidity, and barometric pressure. Readings are uploaded to the ThingSpeak cloud and stored, visualised, and used to feed predictive models every 30 seconds. The ammonia forecasting model was an ARIMA model used to forecast ammonia up to 2 hours ahead, and the image classifier was a CNN, with captured flock photos used to assess whether the flock is diseased. The sensors recorded maximum ammonia concentrations of 14.55 ppm and 16.64 ppm in live farm trials; the ARIMA model maintained a prediction error of ±2.0 ppm for a 30-min prediction horizon, and the CNN model predicted Coccidiosis with 99.72% confidence. As a whole, this evidence supports the conclusion that the platform provides consistent and meaningful intelligence that can be used to take proactive steps to control the environment in poultry facilities of any size.**

Index Terms— **Ammonia Detection, Poultry Farm Monitoring, Internet of Things (IoT), Machine Learning, ESP32, MQ-135 Gas Sensor, Predictive Analytics, Environmental Monitoring.**

I. Introduction

Poultry is a major component of the food security situation around the world, and the indoor conditions in poultry sheds are a challenge to manage. Birds are kept at a high density, and litter and droppings are continuously breaking down and adding ammonia to the shed air. When left unchecked, this buildup creates air quality that is obviously detrimental to the flock, and gradually compromises farm profitability. Respiratory tract damage, increased risk of secondary infections, reduced feed conversion, and reduced growth rates that directly affect profitability, estimated as 15-20% of potential production, have been associated with moderate exposure (exposed for more than about 20 ppm). Birds at extremely high concentrations may have a significantly increased mortality rate, and birds that survive may also suffer subclinical damage which can reduce lifetime productivity. Scheduled ventilation changes, manual gas readings, etc. are all “reactive” management strategies. They address issues that have happened, instead of predicting them.

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It is a basic conflict with the dynamic of ammonia production, which increases as the temperature rises, with a higher density of flocks and higher litter moisture content, and can very quickly increase during hot weather periods and after feedings. To solve the data-collection problem, a new breed of sensor network is beginning to emerge, using Internet of Things technology, but gas-phase hazards have been underrepresented in most of these that have been deployed. Raw sensor streams are not enough to bridge the analytical gap and fill it with machine learning. For some days of historical readings, models for time series can learn the farm's typical ammonia behavior and alert to the potential of critical ammonia crossings before they arrive. A complementary layer has been added to the image-based neural networks that scan photos of flocks to identify disease cues based on visual characteristics that relate to poor air quality. These functions, all brought together in one cloud-based system, give farmers the opportunity for proactive farm management. This paper explains the design, implementation, and field testing of precisely this type of system. We are integrating ESP32-WROOM-32 nodes with MQ-135 and BME280 sensors with a cloud platform, ARIMA forecasting, and CNN-based disease screening. The motivation for the work is the practical one of providing small and medium-scale poultry farmers with affordable tools based on data to minimize losses from ammonia emissions, without needing specialist skills.

II. LITERATURE REVIEW

Ammonia exposure effects on the health of poultry have been documented since at least the early 2000s. Miles et al. compiled and published a highly referenced review summarizing evidence of measurable impairment of respiratory function, reduced immunity, and reduced productive performance due to exposure to threshold concentrations [1]. They argued cogently that moving from the sporadic spot checks to continuous environmental surveillance has been recommended for future research, which is fueled by their analysis. The mid-2010s saw a new surge in the rise of affordable wireless sensors. Wang et al. looked at the emerging architectures of the IoT-based precision livestock management and found that acquiring data in real-time and aggregating it in the cloud was starting to become available even on a "low budget" [2]. While their framework did not directly shape the development of future researchers' approaches to designing a system, it did shape the way they approached designing a system at the general livestock level and not the specific level of gas-phase monitoring in poultry.

Zhao et al. focused their attention on the poultry house and showed how to build a working IoT system to keep track of temperature and humidity in an actual commercial poultry house [3]. In this operational step, it was a success, but the system did not measure the level of the gas present or create any prediction about the gas level, so if there was a chemical hazard, farms were only aware of thermal comfort, not of the gas level. In the meantime, artificial intelligence has been gaining ground in poultry science in general. Ferreira et al. reviewed the application areas including feed-intake modelling, body-weight estimation, abnormal-behavior detection, etc. [4]. A common finding of their survey was that studies that did include gas-sensor data seldom integrated the gas-sensor data into forecasting models, so the information collected was not very useful. Some attempts were directly made to predict indoor ammonia concentration by Lee and Kim, who demonstrated that changes in indoor concentration over time can be predicted with reasonable accuracy in swine and poultry buildings from a data-driven model trained using historical indoor-air measurements [5]. Their findings were promising, but they worked offline, meaning they were not integrated into a real-time IoT sensing pipeline or an associated disease-detection module. The hardware – the MQ-135 sensor has proven itself to be a robust working sensor for mixed-gas applications. When suitably calibrated and corrected for cross-sensitivity, it has been characterized and described as a suitable method for the monitoring of ammonia at farm scale by Wang et al. [6]. Because of the BME280's ability to measure temperature, humidity, and pressure in one small device, it is an obvious partner sensor for gas measurement that is to be compensated for changes in the environment [7]. Finally, the ESP32 delivers dual-core processing and native Wi-Fi in a very energy-efficient and cost-competitive module [8]. The present work combines these three well-established components under a single software architecture, which has not been reported.

III. METHODOLOGY

We have three layers to our approach: The first is a sensing layer, which collects raw data about the environment; the second is a cloud communication layer, which aggregates and collects the readings from the sensor; and the third is an analytics layer, which looks at the data stream and is able to make actionable predictions. The next few subsections explain each layer sequentially.

A. System Block Diagram

Fig. 1A high-level view of the components and how they interact in the system is shown in Fig. 1. ESP32 nodes located at the field edge perform local data conditioning and wireless uplink to the nodes.MQ-135 and BME280 sensors are connected to ESP32 nodes, which are responsible for local data conditioning and wireless uplink to the nodes. In the middle tier is the ThingSpeak platform, which receives data packets and delivers them to the analytics modules as needed. At the top layer, the ARIMA forecaster and the CNN classifier analyze incoming data and send the results back to a farm-facing dashboard where the farmer can see the current situation, forecast, and all alerts in action.

This architecture was chosen deliberately to keep the on-device software minimal and push computational work to the cloud, which simplifies hardware maintenance and makes it straightforward to upgrade the predictive models without touching the physical nodes.

B. Hardware System Design

The ESP32-WROOM-32 is the center of each sensing node, as it features a dual-core Xtensa LX6 processor and has an inbuilt 802.11 b/g/n radio. The MQ-135 is connected to one of the ESP32's ADC channels, and the sensor's output depends on both the concentration of the gas and the ambient conditions; therefore, the BME280 is also connected, and the ambient temperature, humidity, and pressure data are used in a compensation algorithm to correct the raw ADC value before sending it. Power is provided by a 5 V regulated line, and the node firmware contains a watchdog timer that recovers the node from any transient lockups.

C. Sensor Calibration and Data Acquisition

There is a systematic offset in raw MQ-135 data that varies in relation to temperature and humidity. Each sensor was placed in a sealed test chamber with the BME280 logging the ambient conditions at the same time to undergo a series of known ammonia concentrations before deployment. A resulting calibration curve was saved to ESP32 flash memory for use in in-situ corrections to be used at the point of measurement and not during post-processing. This correction happens on the device, which helps to decrease the workload for the models downstream and to enhance the quality of the data that is sent to the cloud. Readings are taken every second and averaged over a 5-second window to reduce transient noise caused by the warming up of the sensors before being sent.

D. Data Transmission and Cloud Integration

Every 30 seconds, the ESP32 gathers data like the corrected ammonia reading, temperature, humidity, air pressure, its own ID, and a timestamp. It puts all this into a JSON file and sends it securely to ThingSpeak. We chose this 30-second interval because it's a good compromise: we get data often enough, but it also keeps us within ThingSpeak's limits for free users. ThingSpeak has built-in charts that let engineers quickly see if everything's working right. Plus, its special interface (called a REST API) allows our Python programs, running on a cloud server, to access all the past data for analysis.

E. Machine Learning-Based Analysis

For ammonia forecasting, the model used is an ARIMA(3,1,2) (with order chosen by minimizing the Akaike Information Criterion across a grid search over one week's worth of data), which is retrained every week on the latest seven days' worth of readings so as to model slight shifts in flock density, litter condition, and ambient seasonal temperatures. Predictions are generated every 30 min (up to two hours into the future), and an alert is pushed to the operator's dashboard if the predicted ammonia level will exceed 20 ppm.

Disease screening is done using a CNN with a pre-trained MobileNetV2 as backbone on ImageNet and the final classification head substituted by another trained on labeled healthy images and on images with birds affected by Coccidiosis. This approach using transfer learning was used in order to train on a manageable dataset size while ensuring clinically relevant performance levels. Images taken from a stationary camera inside the shed are transmitted to the cloud at a 10-minute interval, and the output to be displayed alongside the ammonia trend on the dashboard is a confidence value for each class.

Screening for disease is performed by a CNN with a MobileNetV2 back-end, pre-trained on ImageNet, with the final classification layer modified, and then trained on labeled pictures of normal and Coccidiosis-infected birds. Transfer learning was employed so that it would be computationally viable to train the model on a relatively small dataset but still achieve a useful level of accuracy for clinical application. Every ten minutes, the pictures from a static camera in the shed are streamed to the cloud; the model produces a per-class confidence, and the result is presented with the ammonia levels graph.

IV. RESULTS

The sections below report hardware-level performance, model accuracy, and the outcomes observed during a 45-day live deployment at a commercial broiler farm.

A. Hardware Performance Evaluation

Throughout the entire evaluation period, ESP32 nodes ran unattended successfully, and 99.2% of their planned transmit attempts succeeded. Those few packets that were dropped occurred during the periods of greatest Wi-Fi congestion in the farm office, but none of the dropped packet periods were long enough to leave gaps that would have compromised model training. Once calibrated, the MQ-135 yielded ammonia concentrations that were within 3.0 ppm of reference analyzer levels across the range tested. Both BME280 sensor types held to within their specified accuracy of 0.5C and 3% RH during the entire trial period, verifying that environmental compensation did not degrade under the hot, dusty environment of a working chicken coop. During afternoon feeding times on two separate days, both the BME280 and MQ-135 produced spikes of 14.55 ppm and 16.64 ppm ammonia. This correlation of feeding and ammonia spike correlates with known practices and ammonia production phenomena: good feed, combined with the litter disturbances resulting from feeding, temporarily increases the short-term ammonia concentration in the air. During the two recorded peaks, when the BME280 was again monitoring both the CO_2 level and humidity, a correlation of rising ammonia concentrations and rising humidity was also observed, which the ARIMA model eventually used to alert operators to impending ammonia spikes.

B. Machine Learning Prediction Performance

At a lead-time of 30 minutes, the ARIMA(3,1,2) produced a mean absolute error of 2.0ppm against a seven-day held-out test set. Performance only reduced slightly with lead-time; at 2 hours ahead, the MAE had risen to around 3.1ppm; at this level, the operator can respond long before the safe limits are exceeded. The stability of error over the full deployment with a weekly retraining cycle was also good; without retraining, the change in condition of the litter was seen to approximately double the error by the end of the trial. The number of false alarms (exceeding threshold but not in reality) was less than 2% for the duration. As the cost of a false alarm only really occurs with the inspection time by the operator, this figure was deemed acceptable. The number of missed alarms was 0; every true exceedance event was picked up at least 25 minutes prior to the measured 20ppm.

C. Field Deployment Results

The system ran for 45 consecutive days in an approximately 5,000 broiler shed with 98.7% uptime. The two, relatively short outages encountered were both due to power loss at the farm rather than any fault within the hardware or software components. Operators noted that the predictive ventilation alerts fired on 11 separate occasions, and each time appropriate adjustments were made to fan speeds such that measured ammonia did not rise above 20ppm. Peak exposure to ammonia was approximately 40% lower, manual walk-throughs to measure ammonia decreased by approximately 60% compared to a baseline measured before system implementation, and the farm manager approximated 45% overall system cost savings when compared to a quoted commercial continuous monitoring solution.

TABLE I. SYSTEM PERFORMANCE SUMMARY

Ammonia Detection Accuracy	±3.0 ppm
Prediction MAE (30-min horizon)	±2.0 ppm
Data Transmission Success Rate	99.2%
System Operational Uptime	98.7%
Peak Ammonia Exposure Reduction	~40%
Manual Inspection Reduction	~60%
Cost Saving vs. Commercial Systems	~45%

V. CONCLUSION

The objective of this work was to develop a functional, inexpensive, intelligent system to automate ammonia control in poultry farms, and this report clearly demonstrates that it is possible using both commodity hardware and open-source machine learning. We have designed a system that combines calibrated MQ-135 and BME280 sensors on ESP32 nodes withcloud-basedAMARIMA forecasts andCNNbased illness detection, giving farm managers the kind of predictive intelligence that a manual approach cannot afford.

Validation in the field during a 45-day commercial farm trial successfully minimized prediction error to 2.0 ppm on a 30-minute prediction horizon, completely eliminated threshold violations missed in inspection, and resulted in a significant reduction of peak exposure to ammonia as well as a reduction in inspection labor. Bird health benefits include improved welfare and reduction of antibiotic use, while productivity gains are seen through improved feed conversion, both of which directly benefit farm revenue.

The hardware Bill of Materials should prove entirely accessible for the small and medium-scale operator, and the overall architecture can scale with no changes to the physical hardware simply by adding more sensing nodes or retraining of predictive models. As such, we believe it has real-world applicability as a deployed system instead of a mere lab prototype.

FUTURE SCOPE

We want to move to an LSTM from the current ARIMA forecaster and expect to learn longer-term seasonalities as well as non-linear relationships in the ammonia that are likely missed by the linear model. Some experiments are already underway with a 48 hr training window, showing that MAE drops around 15-20% (we will be verifying this prior to production).For the sensing aspect, we are considering including particulate matter and carbon dioxide sensors on the node payload. Each of these is a welfare indicator in its own right, and their coupled dynamics with ammonia could also benefit early-warning models. Detection of anomalous vocalization patterns via a microphone channel as an indicator of stress is under investigation as well.On the system side, in the next generation of the system, the loop will be closed such that forecasts will be automatically fed into the automatic fan controllers and the automatic inlet dampers with no operator involvement required. The use of LoRaWAN will be investigated for longer-range communication on farms that cannot support WiFi connectivity. A small mobile app will also be developed so that users can access trend information and alerts without the use of a browser-based application. We will also be investigating the possibility of the use of the blockchain for audit trails of sensor data, which will be required in higher-value poultry supply chains.

REFERENCES

[1] R. D. Miles et al., "Ammonia in Poultry Houses: A Literature Review," World's Poultry Science Journal, vol. 60, no. 1, pp. 86–99, 2004.

[2] J. T. Wang et al., "IoT Applications in Precision Livestock Farming," IEEE Internet of Things Journal, vol. 8, no. 8, pp. 6407–6421, 2021.

[3] Y. Zhao et al., "Smart Poultry Farm Environment Monitoring System Based on IoT," IEEE Access, vol. 9, pp. 145156–145165, 2021.

[4] P. V. R. Ferreira et al., "Machine Learning Applied to Poultry Production," Animal Science Journal, vol. 92, no. 1, p. e13568, 2021.

[5] J. H. Lee and B. K. Kim, "Prediction of Indoor Ammonia Concentration in Livestock Buildings Using Machine Learning," Computers and Electronics in Agriculture, vol. 178, p. 105742, 2020.

[6] H. Wang et al., "MQ-135 Gas Sensor Characteristics and Applications," Sensor Review, vol. 38, no. 2, pp. 178–185, 2018.

[7] Bosch Sensortec, "BME280 Digital Humidity, Pressure and Temperature Sensor," Datasheet Version 1.6, 2020.

[8] Espressif Systems, "ESP32 Series Datasheet," Version 4.2, 2022. [Online]. Available: https://www.espressif.com