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Early Escherichia coli prediction in broiler chickens

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ABSTRACT

Poultry farming remains an important contributor to global food security and commercial livestock production. However, infectious diseases such as Escherichia coli (E. coli) cause mortality, poor feed efficiency, reduced growth performance, and economic losses in broiler production systems. This study proposes a checkpoint-based multimodal transformer-convolutional neural networks (CNN) framework for early flock-level E. coli infection risk prediction using environmental, production, behavioural, and visual poultry data. Flock monitoring records collected from 2022 to 2025 were structured across six production checkpoints: day 3, day 7, day 14, day 21, day 28, and day 31. After long-format conversion, approximately 90,000 temporal observations were used for transformer modelling, with 72,000 records for training and 18,000 for testing. The CNN component evaluated 249 poultry images across healthy, low-risk, medium-risk, high-risk, and non-broiler classes. The transformer model achieved 99.96% accuracy, while the CNN model achieved 95.58% accuracy. The integrated dashboard generated flock risk scores, contributing factors, alerts, gradient-weighted class activation mapping (Grad-CAM) explanations, and veterinary advisory recommendations, demonstrating the potential of multimodal artificial intelligence (AI) for proactive poultry health monitoring.

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1. INTRODUCTION

Poultry farming remains one of the most important agricultural sectors contributing toward global food security, nutrition, and commercial livestock production [1]. Broiler chickens represent a major source of affordable animal protein worldwide; however, commercial poultry production systems continue to face significant challenges associated with infectious disease outbreaks and environmental management [1], [2]. Among bacterial diseases affecting poultry production, Escherichia coli (E. coli) infections remain particularly important due to their association with increased mortality, reduced growth performance, poor feed conversion efficiency, carcass condemnation, and substantial economic losses [1], [2].

Traditional poultry disease detection approaches rely primarily on manual observation, laboratory testing, and visible clinical symptoms [3]. These approaches are reactive and often identify disease only after infection has progressed significantly, limiting opportunities for timely intervention. The real problem addressed in this study is therefore the absence of a transparent, flock-level early-warning framework that can combine environmental stress, production decline, behavioural change, and visual symptoms before severe clinical deterioration occurs. Recent advances in artificial intelligence (AI), machine learning, and precision agriculture have enabled the development of automated poultry monitoring systems capable of supporting early disease prediction and intelligent decision-making [4], [5]. Technologies such as computer vision, internet of things (IoT) sensors, and audio-based monitoring systems have increasingly been applied within poultry farming environments to improve disease surveillance and production management [6]–[8]. Commercial poultry operations primarily monitor flock-level environmental and production indicators rather than individual bird physiological measurements. Recent advances in computer vision, machine vision, and other non-invasive monitoring technologies have demonstrated considerable potential for early poultry health prediction, welfare assessment, and production monitoring within precision poultry farming systems [9], [10].

Deep learning approaches, particularly convolutional neural networks (CNNs), have demonstrated strong performance in poultry disease classification using image-based analysis [1], [11], [12]. Deep learning-based poultry diagnostic systems have increasingly demonstrated strong potential for automated disease monitoring and intelligent decision support [13]. Recent studies have also explored multimodal approaches integrating visual and audio data for poultry health monitoring [14], [15]. In addition, object detection models such as You Only Look Once (YOLO) have been successfully applied for automated poultry disease detection and behavior monitoring [16], [17]. Other recent studies have also demonstrated that multimodal CNN-based feature fusion techniques can significantly improve poultry health classification performance [18]. Environmental monitoring systems utilizing IoT technologies further contributed toward continuous monitoring of poultry house conditions including temperature, humidity, ammonia, and carbon dioxide levels [7], [4]. Audio-visual deep learning approaches have also been explored for intelligent poultry disease monitoring within smart farming environments [15]. Machine learning and optimization-based disease prediction methods have also demonstrated promising capability for early poultry disease diagnosis [19]. Despite these advancements, most existing systems remain unimodal and focus primarily on detecting visible symptoms rather than proactively predicting disease onset [2], [3]. Furthermore, limited research has explored the integration of temporal sequence modeling and explainable artificial intelligence (XAI) within poultry disease prediction systems. Ensemble CNN approaches have also been explored for poultry disease detection from faecal images, further showing that visual diagnostic pipelines can benefit from model diversity and comparative benchmarking [20].

Transformer architectures have recently gained attention for their ability to model long-range temporal dependencies using self-attention mechanisms [21]. Their application within poultry disease prediction remains limited, particularly in multimodal frameworks integrating environmental, production, and visual data simultaneously. In addition, many existing AI-based poultry disease systems lack interpretability, reducing trust and limiting practical adoption in real-world farming environments [5], [22]. XAI techniques therefore play an important role in improving transparency and supporting informed decision-making.

Conceptually, the proposed multimodal learning approach is grounded in representation learning and information fusion theory, where complementary data streams are transformed into shared latent representations that improve prediction under uncertainty. In computer science terms, the transformer branch models temporal dependencies through self-attention, the CNN branch extracts spatial health features from images, and the fusion layer integrates these heterogeneous signals into a unified decision space. This theoretical grounding connects the study to broader AI research on multimodal representation learning, interpretable predictive modelling, and decision-support systems for information-rich environments [21], [23].

This study proposed a multimodal transformer–CNN framework for early flock-level prediction of E. coli infection in broiler chickens. The proposed framework integrated flock-level environmental, production, and visual data to support proactive infection risk prediction while incorporating XAI techniques to improve interpretability and transparency. A streamlit-based dashboard prototype was also implemented to provide real-time decision support for poultry health monitoring. The main contribution of this study lies in the integration of transformer-based temporal modeling, CNN-based visual analysis, and XAI within a unified multimodal framework for proactive poultry disease prediction.

2. METHOD

2.1. Research design

This study adopted a quantitative experimental research design combined with multimodal AI system development principles to develop and evaluate a checkpoint-based poultry health monitoring framework for early E. coli infection risk prediction in broiler chickens. Quantitative methodology was selected because the study relied on measurable environmental, production, behavioural, and visual poultry variables to train and evaluate deep learning models capable of identifying disease-related flock deterioration patterns [4], [7], [24]. The study further adopted an experimental modelling approach involving dataset development, preprocessing, model training, multimodal fusion, system testing, and dashboard deployment. The proposed framework integrated transformer-based temporal modelling with CNN-based visual poultry assessment to improve flock-level disease surveillance capability within commercial broiler production environments.

2.2. Data acquisition and dataset development

Environmental, production, and behavioural poultry monitoring data were acquired from commercial broiler production cycles recorded between 2022 and 2025. Monitoring focused on six production checkpoints: day 3, day 7, day 14, day 21, day 28, and day 31. Environmental variables included temperature, humidity, ammonia concentration, and carbon dioxide levels, while production variables included flock weight, feed intake, water intake, cumulative mortality percentage, and feed conversion ratio (FCR). Behavioural indicators captured activity and ventilation status. The checkpoint records were converted into approximately 90,000 long-format temporal observations for transformer modelling, supporting an 80:20 split of 72,000 training records and 18,000 testing records.

2.3. Data preprocessing

Before model development, the datasets underwent preprocessing to improve data quality and training stability. Environmental and production variables were cleaned to remove inconsistent records and missing values, while numerical features such as temperature, ammonia concentration, mortality percentage, and FCR were normalized to ensure consistent feature representation during training. The poultry image dataset underwent preprocessing procedures including resizing, normalization, augmentation, and tensor conversion [5], [14]. Images were resized to standardized dimensions compatible with the CNN architecture, while augmentation techniques such as image rotation, horizontal flipping, and brightness adjustment were applied to improve dataset variability and reduce overfitting. Following preprocessing, the flock dataset was converted from wide checkpoint format into long-format sequential observations to support transformer-based temporal learning. Checkpoint-based temporal sequences enabled the transformer model to analyse progressive environmental and production changes across the monitored broiler production stages.

2.4. Proposed multimodal framework

The proposed framework adopted a checkpoint-based multimodal architecture integrating transformer-based temporal modelling with CNN-based visual poultry assessment. The system was designed to combine environmental monitoring, production analysis, behavioural assessment, and poultry image classification within a unified flock-level prediction framework. The transformer model functioned as the primary temporal prediction engine responsible for learning sequential flock progression patterns associated with environmental deterioration, mortality progression, declining production performance, and elevated infection risk conditions. Simultaneously, the CNN component functioned as a supportive visual poultry assessment mechanism responsible for identifying visible poultry abnormalities associated with unhealthy flock conditions [2], [5], [15]. Outputs generated from the transformer and CNN branches were integrated through a multimodal fusion layer responsible for generating final flock-level infection risk classifications categorized into low-risk, medium-risk, and high-risk conditions.

2.5. Transformer-based temporal modelling

The transformer model was implemented to analyse checkpoint-based environmental, production, and behavioural poultry monitoring data. The model utilized self-attention mechanisms capable of learning temporal relationships between historical checkpoint observations and future infection risk outcomes [23]. Input features included temperature, humidity, ammonia concentration, carbon dioxide levels, flock weight progression, feed intake, cumulative mortality percentage, FCR, and flock activity indicators. Sequential checkpoint observations were transformed into temporal feature representations before being processed through the transformer encoder layers. The self-attention architecture enabled the model to identify important sequential relationships associated with environmental stress, declining production performance, and elevated flock health risk conditions. The final transformer output generated temporal feature embeddings used during multimodal fusion and final flock-level risk prediction.

2.6. CNN-based visual poultry assessment

The CNN component was incorporated to support visual poultry health assessment using image data grouped into five classes: healthy, low-risk, medium-risk, high-risk, and non-broiler. Images were resized to 224×224 pixels, normalized, and augmented through rotation, flipping, zooming, and brightness adjustment. The CNN focused on visual cues such as weak posture, feather deterioration, swelling, low activity, and poultry distress indicators. Gradient-weighted class activation mapping (Grad-CAM) explainability visualizations were incorporated to show image regions that contributed most strongly to CNN predictions.

2.7. Multimodal fusion procedure

The outputs generated by the transformer and CNN models were combined through decision-level multimodal fusion. The transformer produced probability scores for low-, medium-, and high-risk flock categories from checkpoint monitoring data, while the CNN produced visual probability scores from poultry images. These outputs were converted into weighted risk scores and mapped to low-, medium-, or high-risk bands for final flock-level classification. This fusion strategy preserved interpretability while combining temporal and visual evidence for decision support.

2.8. Model training and testing procedure

The checkpoint-based temporal dataset was divided using an 80:20 train-test split, resulting in 72,000 training records and 18,000 testing records from approximately 90,000 long-format observations. The transformer model was trained with the Adam optimizer and cross-entropy loss. The CNN model was evaluated on 249 images across healthy, high-risk, low-risk, medium-risk, and non-broiler classes. Model performance was evaluated using accuracy, precision, recall, F1-score, confusion matrices, confidence scores, and Grad-CAM visual explanation outputs.

2.9. Dashboard implementation

The developed multimodal poultry health monitoring framework was implemented within a streamlit-based dashboard environment designed to support practical flock monitoring and intelligent disease surveillance. The dashboard enabled users to input flock-level environmental and production variables, upload poultry images for visual assessment, and receive flock-level infection risk predictions together with environmental alerts and veterinary advisory prompts. Additional functionalities incorporated into the dashboard included checkpoint progression monitoring, confidence scoring, Grad-CAM explainability outputs, and emergency reassessment capability. These features improved the practical usability and interpretability of the developed framework within commercial poultry production environments.

2.10. Methodological limitations and validation scope

The study relied on checkpoint-based production records and manually collected monitoring variables, which may introduce sampling bias, observer bias, and site-specific management effects. Although conversion to long-format sequential observations increased the number of training samples, it did not remove the need for larger multi-farm validation using independently collected commercial datasets. Future work should replicate the framework using automated IoT sensor streams, continuous environmental logging, and larger image datasets collected across different breeds, housing systems, production seasons, and geographic regions. Comparative evaluation against long short-term memory (LSTM) networks, temporal convolutional networks, attention-based hybrids, and federated learning architectures would further strengthen methodological rigor and clarify the relative advantage of the proposed transformer-CNN fusion strategy.

3. RESULTS

This section presents the experimental results obtained from evaluating the proposed checkpoint-based multimodal transformer-CNN poultry health monitoring framework. Results are reported first, followed by a separate discussion that interprets the findings in relation to prior work, methodological limitations, explainability, and practical deployment.

3.1. Dataset risk distribution analysis

The dataset risk distribution analysis revealed that the checkpoint-based flock monitoring dataset contained varying proportions of low-risk, medium-risk, and high-risk flock observations. As illustrated in Figure 1, low-risk flock records constituted the largest proportion of the dataset, followed by medium-risk observations, while high-risk flocks represented the smallest proportion of records. This distribution reflects realistic commercial poultry production environments where healthy flock conditions generally occur more frequently than severe disease outbreak conditions.

3.2. CNN poultry image dataset analysis

The CNN poultry image dataset analysis demonstrated variability across five visual classes: healthy, low-risk, medium-risk, high-risk, and non-broiler images. The evaluation subset contained 249 images, with healthy and high-risk categories more strongly represented than the low- and medium-risk categories. This distribution improved the model's ability to identify clear healthy and high-risk visual patterns but limited recall for intermediate categories. The distribution of image classes is presented in Figure 2.

This distribution reflects the study's emphasis on visual health assessment rather than direct pathogen identification. Healthy birds generally showed upright posture, normal feather condition, and active appearance, while elevated-risk images showed weak posture, feather deterioration, reduced activity, swelling, or visible distress. The image class imbalance was important for interpretation: the CNN achieved strong performance for healthy, high-risk, and non-broiler images, but low-risk and medium-risk classes remained more difficult because intermediate health states often share subtle features with both healthy and high-risk birds.

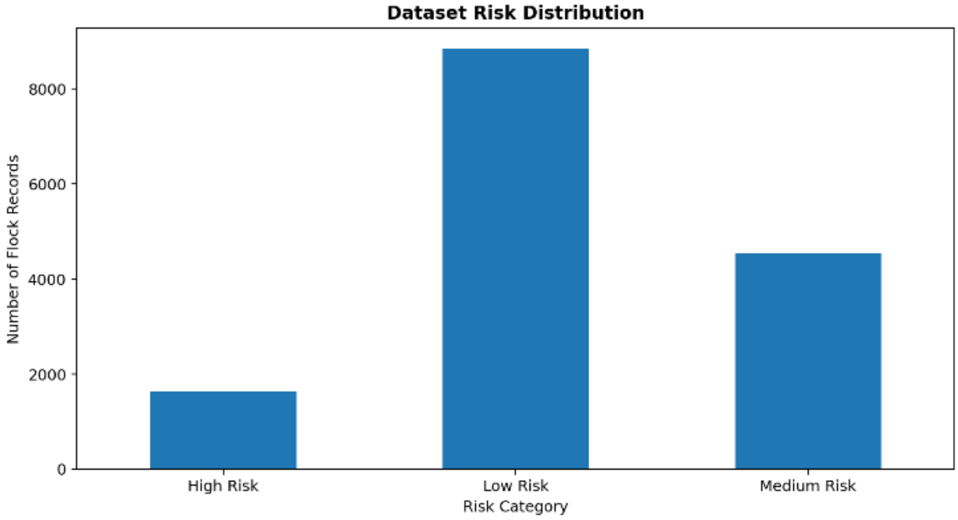

Figure 1. Dataset risk distribution

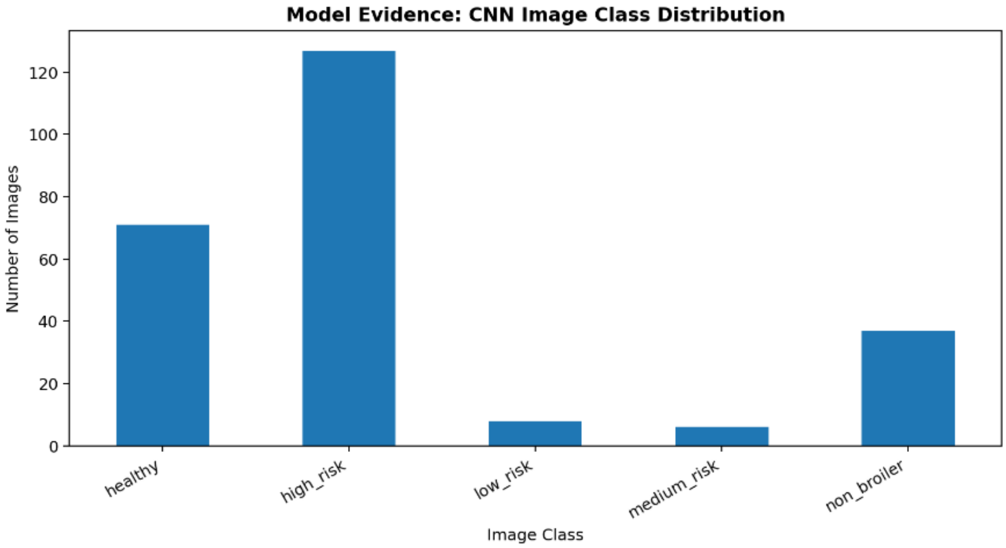

Figure 2. Image class distribution

3.3. Mortality progression across production checkpoints

The mortality progression analysis demonstrated gradual increases in average flock mortality percentage across the monitored broiler production checkpoints. As illustrated in Figure 3, mortality levels remained relatively low during the early production stages including day 3 and day 7 but progressively increased during later checkpoints, particularly between day 21 and day 31.

This trend suggests that flock deterioration and elevated infection risk conditions become increasingly visible during the later stages of the broiler production cycle where environmental stress, stocking density, and waste accumulation intensify. The observed mortality progression patterns validate the importance of checkpoint-based temporal monitoring within the proposed transformer-based prediction framework. By analysing sequential checkpoint observations, the transformer model was able to learn temporal relationships between historical flock conditions and future infection risk outcomes. Mortality progression therefore functioned as an important early-warning indicator associated with declining flock health conditions and worsening environmental quality within commercial poultry production environments.

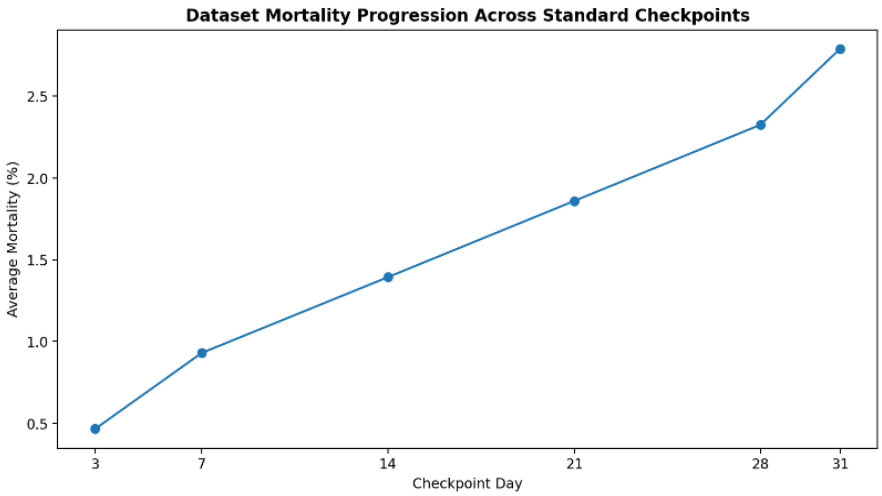

Figure 3. Dataset mortality progression

3.4. Feed conversion ratio trend analysis

The FCR trend analysis revealed clear differences between healthy and elevated-risk flock categories across the monitored production checkpoints. As illustrated in Figure 4, low-risk flocks consistently maintained lower and more stable FCR values throughout the production cycle, indicating efficient feed utilization and healthy growth progression.

Conversely, medium-risk and high-risk flocks demonstrated progressively worsening FCR values during later production stages. High-risk flocks particularly exhibited the highest FCR deterioration between day 21 and day 31, suggesting reduced production efficiency and declining physiological performance associated with elevated infection risk and environmental stress conditions. The increasing divergence between healthy and elevated-risk FCR trends across later checkpoints further demonstrates the importance of production monitoring variables within flock-level disease surveillance systems. These findings indicate that declining feed efficiency may function as an important physiological indicator of stress, weakened immunity, and progressive flock health deterioration within commercial broiler production environments.

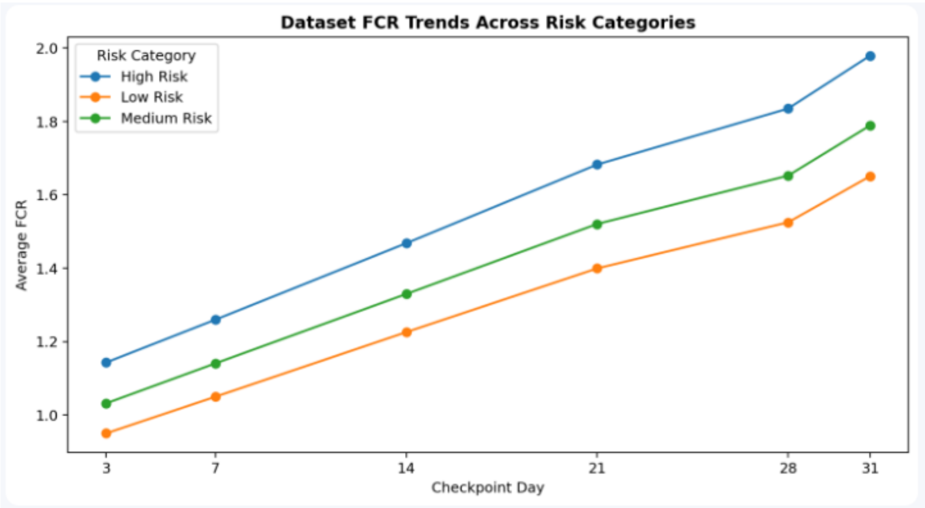

Figure 4. FCR trend

3.5. Environmental correlation analysis

The environmental correlation heatmap demonstrated strong relationships between environmental deterioration and declining production performance indicators within the checkpoint-based flock monitoring dataset. As illustrated in Figure 5, positive correlations were observed between ammonia concentration, carbon dioxide levels, mortality percentage, and worsening FCR values.

Ammonia concentration demonstrated particularly strong relationships with carbon dioxide accumulation and mortality progression, suggesting that inadequate ventilation and poor environmental management contribute significantly toward declining flock health conditions. Elevated temperature levels also demonstrated positive relationships with increasing mortality percentage and worsening production efficiency. These findings reinforce the biological relevance of environmental monitoring variables within intelligent poultry disease surveillance systems and support the inclusion of environmental indicators within the proposed multimodal transformer–CNN framework.

The correlation analysis further demonstrated that environmental stress conditions are closely interconnected with production decline and flock deterioration. Consequently, continuous environmental monitoring may provide valuable early-warning information capable of supporting proactive poultry health management and reducing disease-related production losses within commercial broiler farming environments.

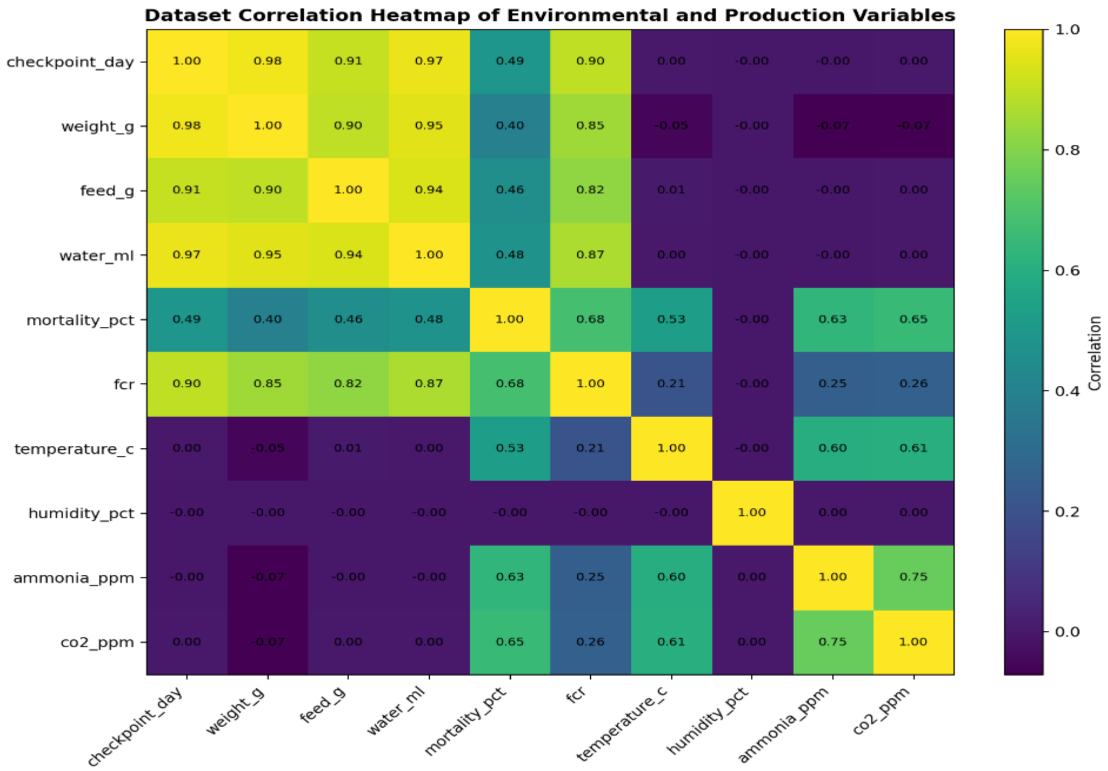

Figure 5. Environmental correlation

3.6. Ammonia concentration and mortality relationship

The ammonia concentration and mortality relationship analysis demonstrated that increasing ammonia levels were generally associated with elevated flock mortality percentages across the monitored production checkpoints. As illustrated in Figure 6, lower ammonia concentrations were primarily associated with relatively stable mortality levels, while elevated ammonia concentrations demonstrated increased mortality variability and worsening flock health conditions.

High ammonia concentration levels are commonly associated with poor poultry house ventilation, litter deterioration, respiratory stress, and weakened immunity within commercial poultry production systems. The observed relationship between ammonia accumulation and increasing mortality progression therefore supports the role of environmental stress as a major contributing factor toward declining poultry health conditions and increased susceptibility to bacterial infections such as E. coli.

The findings additionally reinforce the importance of integrating environmental monitoring into intelligent poultry disease surveillance systems. By continuously monitoring ammonia concentration and related environmental variables, the proposed multimodal framework was able to identify deteriorating flock conditions capable of contributing toward elevated infection risk within commercial broiler production environments.

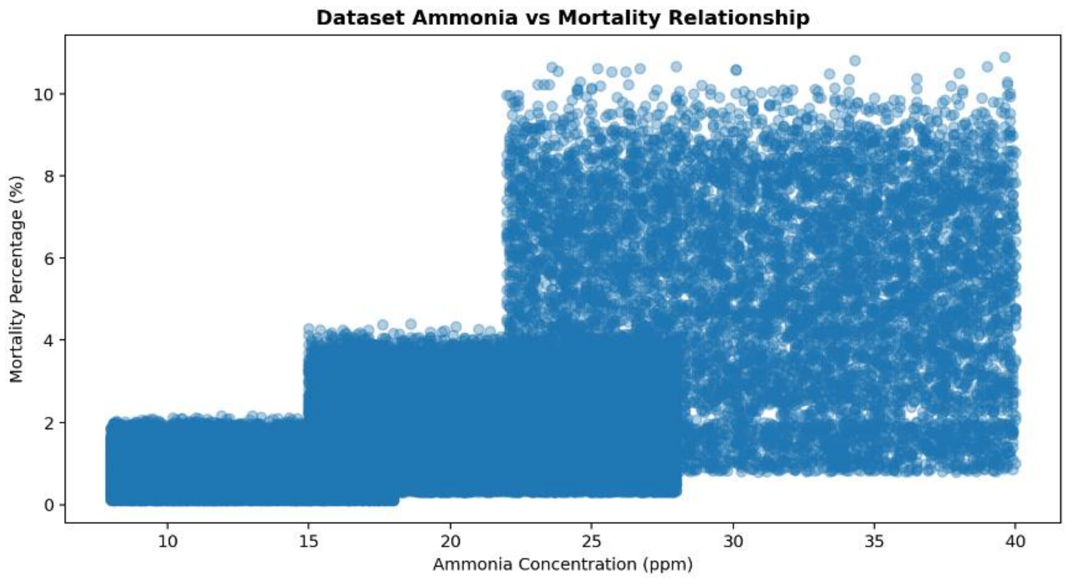

Figure 6. Ammonia vs mortality

3.7. Multimodal framework classification performance

The model evaluation demonstrated strong classification performance across the temporal and visual components. The transformer model achieved 99.96% accuracy on 18,000 testing observations, with weighted average precision, recall, and F1-score values of 99.96%. Class-level transformer performance remained high across high-risk, low-risk, and medium-risk groups, with F1-scores of 99.90%, 99.99%, and 99.94%, respectively. The CNN model achieved 95.58% accuracy on 249 evaluation images, with weighted average precision of 96.00%, recall of 96.00%, and F1-score of 95.00%. It correctly classified all 71 healthy images and all 37 non-broiler images, classified 123 of 127 high-risk images correctly, and achieved 50.00% class accuracy for both low-risk and medium-risk images. These results confirm strong visual discrimination for clear classes while highlighting the difficulty of distinguishing intermediate visual risk states.

In the integrated dashboard example, the multimodal system classified the flock as high-risk with a risk score of 0.85. The main contributing factors included high ammonia, humidity, feed intake, water intake, and ventilation conditions, after which the dashboard generated alerts, confidence information, and veterinary advisory recommendations. Figure 7 presents the confusion matrix of the multimodal flock risk classification.

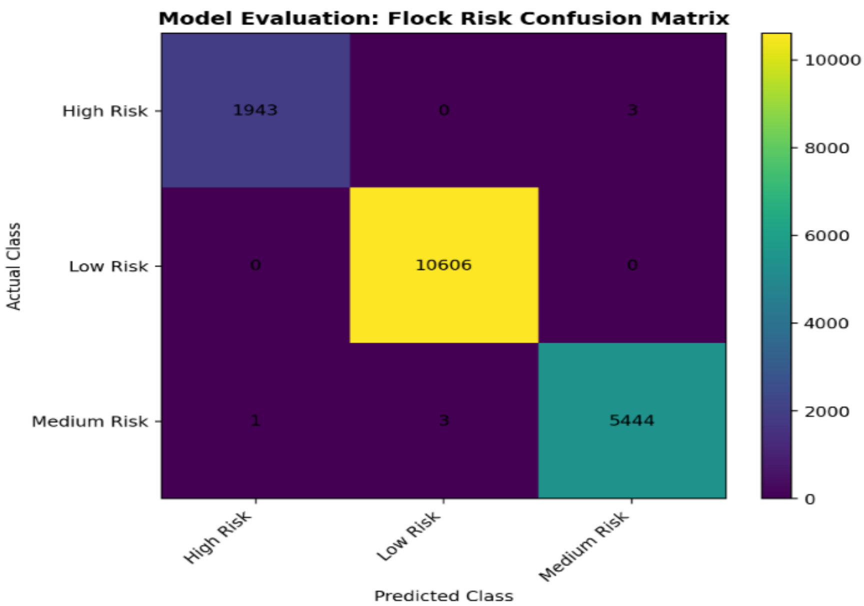

Figure 7. Flock risk confusion matrix

The low-risk temporal category demonstrated particularly strong classification consistency, while the CNN results showed that low-risk and medium-risk visual categories were harder to separate. This overlap is practically meaningful because intermediate disease progression may produce subtle visual features and similar environmental-production trajectories before severe deterioration becomes obvious. Future refinement should therefore use larger balanced image datasets, longer temporal windows, calibrated decision thresholds, and attention-weight analysis to improve separation of intermediate and severe risk conditions.

4. DISCUSSION

4.1. Interpretation of overall findings

Overall, the experimental evaluation demonstrated that checkpoint-based temporal modelling was highly effective for flock-level risk prediction, with the transformer achieving 99.96% accuracy on 18,000 testing observations. The CNN contributed complementary visual evidence, achieving 95.58% accuracy on 249 images and performing strongest on healthy, high-risk, and non-broiler classes. Together, the models captured relationships between environmental deterioration, production decline, behavioural abnormalities, and visible health cues.

The results further demonstrated the practical feasibility of applying multimodal AI techniques within precision poultry farming and intelligent livestock health monitoring systems. The developed framework therefore provides strong potential for supporting proactive flock health management, early disease surveillance, and intelligent poultry production decision-making within commercial broiler farming environments. Compared with prior poultry AI studies that emphasize single data streams such as images, audio, or environmental sensors, the present framework contributes a checkpoint-based multimodal design that links temporal production progression with CNN-based visual assessment and XAI outputs [13]–[18]. This integration is the main novelty of the study: it shifts the prediction task from late symptom recognition toward proactive flock-level risk estimation supported by interpretable evidence.

The explainability outputs should be interpreted alongside the numerical risk predictions rather than as separate visual artifacts. Grad-CAM visualizations can indicate whether the CNN branch focuses on biologically meaningful regions such as posture, feather condition, and visible distress, while temporal attention patterns can help identify which checkpoint variables contribute most strongly to the final risk class. Combining these explanation channels supports trust, enables veterinary review, and helps farmers understand whether risk is driven primarily by environmental deterioration, production decline, or visual abnormality.

From a deployment perspective, the framework can inform IoT-enabled poultry monitoring by connecting ammonia, temperature, humidity, carbon dioxide, water intake, feed intake, mortality, and image feeds to a cloud-based dashboard for real-time alerts. Such a system could support farm-level intervention decisions, regional disease surveillance, and national livestock health policy by generating earlier warning signals for environmental stress and possible bacterial disease progression. Cloud deployment and federated learning could further allow farms to improve shared models without exposing sensitive production records, while reinforcement learning may support future decision rules for ventilation adjustment, litter management, and veterinary response strategies [25].

5. CONCLUSION

This study developed and evaluated a checkpoint-based multimodal transformer-CNN framework for early flock-level prediction of E. coli infection in broiler chickens. The findings support the value of multimodal learning, XAI, and dashboard-based decision support for proactive poultry health management. The framework can be adapted beyond E. coli prediction to other poultry diseases where environmental stress, production decline, behavioural changes, and visible symptoms develop progressively over time, including respiratory disease, avian influenza risk monitoring, and broader flock welfare surveillance. Future research should validate the approach on larger multi-farm datasets, integrate automated IoT and cloud-based data streams, compare additional deep learning architectures such as LSTMs and hybrid attention models, and strengthen explainability outputs for practical veterinary and policy use.

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C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [NC], upon reasonable request.

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