Impact of Climate Change on Animal Diseases Based on Machine Learning

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***Abstract*—The rapid pace of climate change has altered the distribution of animal diseases, increased their frequency, and dispersed them over a larger geographic area. Rising temperatures, fluctuating humidity, and erratic rainfall patterns have increased the risk of illness in cows. These modifications have facilitated the growth of diseases and vectors. As a result, timely and accurate identification of these illnesses has become crucial for both food security and sustainable animal health management. To detect and classify animal diseases using visual data, this study proposes a diagnostic framework that utilizes machine learning approaches, with a focus on convolutional neural networks (CNNs) in conjunction with classification models, including ResNet, YOLOv5, and AltCLIP. By learning to distinguish between healthy and sick animals, the model enables prompt identification and treatment of sick animals. Merging data on disease detection with climate parameters, we make comparisons between them to get the best result and use this to generate advanced tools for detecting diseases. This informs us about potential risks. According to the results, machine learning-based diagnosis can improve disease detection's accuracy and efficiency while also providing important new information for climate adaptation strategies in cattle management. The optimal model will produce a graphical user interface (GUI) that displays environmental risk scores, diagnostic data, and recommendations for actions such as monitoring the situation, seeking immediate veterinary care, or verifying the animal's health.**

Keywords—Climate change; environmental health; convolutional neural network (CNN); animal diseases; graphical user interface (GUI)

I. Introduction

To prevent epidemics and safeguard the health of animals, illness prediction is crucial. Farmers can avoid suffering and financial loss by taking preventive action as soon as possible, thanks to early detection. Additionally, it contributes to the preservation of wildlife, the food chain, and global health initiatives [1]. Predicting illnesses also encourages research and development, which results in new treatments and vaccines.

A. Significance of Disease Prediction

Anticipating potential illness in animals is essential for epidemic management and the preservation of animal health [2, 3]. Timely detection allows farmers to swiftly adopt preventive strategies, thereby reducing their distress and economic losses. Furthermore, it protects animals, supports global health security efforts, and guarantees the integrity of the food supply chain.

B. The Essence of Disease Prediction in Animals

A proactive approach to ensure animal health is to anticipate potential diseases. It functions as a sentinel, identifying potential health concerns prior to their emergence [4]. Prompt intervention can mitigate distress and financial expenditure due to this prior awareness [5]. It strengthens the foundations of our food supply chain to guarantee its safety and reliability, akin to a sentinel. Furthermore, it maintains the complex network that illustrates the interdependence of all life by linking the well-being of humans, animals, and the environment. This proactive strategy fortifies against developing health challenges, enhances compliance with regulations, and elevates awareness of ethical pet ownership [6]. Disease prediction serves as a beacon, guiding humans and animals towards more harmonious and healthier coexistence. Forecasting animal diseases is an essential aspect of a robust ecosystem in its own distinct manner [7].

Preserving the equilibrium between nature and human endeavors contributes to the safeguarding of endangered species and the vitality of animal populations [8]. It functions as a vigilant sentinel, identifying and mitigating zoonotic threats to safeguard global health security and avert possible pandemics. This proactive strategy also cultivates innovation, leading to the development of novel vaccinations, medicines, and diagnostic tools [9]. Disease prediction underscores the need for early identification and treatment by cultivating a culture of readiness and accountability through continuous vigilance. Ultimately, it illustrates our collective commitment to enhancing the quality of life for all and fostering global peace.

C. Machine Learning's Role in Disease Prediction

The Principles of Predicting Animal Diseases: By predicting animal diseases, we can protect their health before they happen. Machine learning is poised to become an integral part of clinical diagnosis, enhancing the accuracy and efficiency of medical evaluations and treatments. [10]. It looks out for your health problems before they happen, like a guardian angel. This knowledge lets you respond quickly, which reduces pain and financial loss [11]. It guards the pillars of our food supply chain like a sentinel to make sure it is secure and reliable [12]. It also protects the complex network that connects the health of people, animals, and the environment, showing how all living things are connected. This progressive approach also makes people more likely to follow the rules, learn more about how to care for pets, and protect us all from new health problems. Essentially, predicting disease is like a beacon that shows people the road to a calm and healthy life [13]. For disease prediction, machine learning is very important since it uses data to find patterns and make accurate predictions. It lets you look at a lot of data, from genetic markers to environmental factors, to find early signs of illness [14]. Machine learning models can find little connections that people would miss by using advanced algorithms [15]. This makes it possible to create predictive models that can figure out how likely it is that a person or group of people will get sick. Also, these models can change and get better over time as more data is collected, making them more reliable and accurate. Machine learning changes how people understand and process information. It is also a powerful tool for keeping an eye on and stopping diseases before they happen. This leads to better results for both people and animals. The effects of climate change on diseases affecting cattle and other animals, along with the introduction of novel infectious organisms, remain inadequately researched.

II. Literature Review

A. Applications of Machine Learning in Animal and Veterinary Public Health Surveillance

Machine learning (ML) is a type of artificial intelligence that employs algorithms to improve its ability to reach a certain goal (such as categorization or prediction) directly from the data itself, without needing explicit and detailed instructions on how to do so [17]. Monitoring systems for zoonotic and animal diseases depend on a range of tasks being done well, and some of these tasks can be done by machine learning algorithms. Machine learning has become a lot more common in veterinary and animal public health surveillance in the past few years, just like it has in other fields. ML algorithms are being used to solve tasks that were unfeasible before big datasets, new ways to look at them, and more computing power were available.

B. Disease Prediction Using Machine Learning Algorithms: KNN and CNN

People today suffer from a variety of diseases because of their lifestyle choices and the environment. Therefore, it becomes crucial to predict the disease early on. However, the doctor finds it too challenging to provide an accurate diagnosis based just on symptoms. Making accurate disease predictions is one of the most challenging tasks [18]. To solve this issue, data mining plays a crucial role in disease prediction. The amount of data in medical science is growing significantly every year. The increasing amount of data in the medical and healthcare domains has made accurate medical data analysis beneficial for early patient care. To find concealed information in massive amounts of medical data, data mining employs sickness data. The patient's symptoms led us to provide a general illness prediction. Accurate disease prediction is achieved using machine learning techniques such as K-Nearest Neighbor (KNN) and convolutional neural networks (CNN). For prediction, a dataset of disease symptoms was required [16]. A person's daily routine and medical history are considered to make an accurate general illness diagnosis. With an accuracy of 84.5% in 2025, the role of machine learning in infectious disease early detection and prediction in the MENA region, CNN performs better than the KNN method in the general disease prediction task. Furthermore, compared to CNN, KNN uses more memory and time.

C. Comparative Study of IoT- and AI-Based Computing Disease Detection Approaches

The growth of several computing methods, such as cloud-, fog-, and edge-based Internet of Things (IoT) systems, has enabled the creation of intelligent sickness detection systems. Because models using deep learning have outperformed shallow learning when handling large volumes of data, the research community has focused more on them than on other machine learning models [19]. However, there hasn't been a comprehensive examination of computer-based and Internet of Things-related systems that employ deep learning techniques for disease diagnosis. To assess different machine learning and deep learning algorithms, as well as their hybrid and optimized algorithms for IoT-based disease detection, this study used the most recent publications on IoT-based disease detection systems that utilize computing technologies, such as cloud, edge, and fog. Their work focused on an IoT architecture for deep learning that may be used to detect diseases. It also recognizes that to develop more efficient IoT sickness detection systems, researchers must concentrate on several factors. This work may be helpful to researchers who want to enhance hybrid IoT-based illness detection and prediction systems that rely on deep learning.

D. "Cattle Disease Identification Using Prediction Techniques"

In developing nations like India, Bangladesh, Nepal, and many others, dairy farming was one of the first forms of occupation. One of the main factors contributing to the increase in productivity in dairy production is dairy farm automation. Numerous illnesses can affect cattle, some of which can reduce output and the quality of dairy products [20]. If not detected early, these illnesses can also lead to livestock mortality, which is significantly hampered by the country's economy's steady growth [21]. Cattle are present in considerable numbers in dairy products. Taking care of them and monitoring the dairy cow's health is simply too difficult. Additionally, the dairy owner and the local government are crucial to this endeavor. The primary characteristic of a health management approach is the ongoing monitoring of each cow's health, prompt diagnosis, and early handling of ill animals. We track the fundamental elements of animal activity, such as temperature, heart rate, etc., using sensor technology. To determine whether an impending disease episode is anticipated, this data is combined and fed into a data mining algorithm. It increases the possible expenses of animal health care as well as the lowest level of veterinarian examination. This study offers a method that describes how IOT and data mining can be used to identify uncommon cow illnesses in farm animal hospitals with affordable treatment options. Animal Disease Prediction using Machine Learning Techniques. In recent years, there has been a significant increase in the variety of animal diseases. Many of these illnesses have a propensity to become zoonotic diseases, which can affect both humans and animals and prove to be highly contagious [22]. The study of having machines or computers learn on their own so that additional predictions can be made is known as machine learning, produced for a variety of uses [23]. Machine learning techniques for human disease identification have been around for a while, but there haven't been many developments for animal diseases. By using machine learning approaches to categorize certain animal diseases and forecast their spread, we bring a novel contribution to the subject with this research study [24]. When animal sickness develops into zoonosis, it can significantly affect both human and animal populations. Therefore, as part of this investigation, we also employed specific methods to determine whether the illness is zoonotic. Keywords: classification, regression, machine learning, zoonosis, and research.

E. Artificial Intelligence and its Application in Animal Disease Diagnosis

The current study looks at the rules, history, subfields, and real-world applications of artificial intelligence in animal disease detection. There are two subfields of artificial intelligence (AI), or intelligence displayed by machines: machine learning and deep learning. In machine learning (ML), algorithms are used to find patterns in data and build a model for future forecasting [25]. Among the most popular algorithms are support vector machines, K-nearest, decision trees, random forests, and linear regression. The four categories of deep learning methods are sparse coding, restricted state machines, convolutional neural networks, and autoencoders [26]. One of the most widely used methods, Convolutional Neural Networks (CNN), automatically recognizes important elements without the need for human supervision. AlexNet, ZFNet, GoogLeNet, VGG-16, and other impressive CNN architectures were on display during the ImageNet Large Scale Visual Recognition Challenge (ILSVRC). The National Animal Disease Referral Expert System (NADRES) of ICARE-NIVEDI, the identification of left atrial enlargement on canine thoracic radiology, the prediction of survivability and the necessity of horses with colic, and the machine learning-based detection of subclinical mastitis in cows by Ebrahimi et al. are a few examples of the documented evidence of AI's application in veterinary sciences [27].

There are many methods used for detecting animal diseases. In this study, different types are chosen to get the highest result for the problem and make a comparison for building a hybrid model to collect data from animals, such as pictures, and climate change parameters. There are two phases of the first set of traditional deep learning, and then we get the advanced one to compare the results.

III. Methodology

The methodology employed in this research aimed to create and assess a resilient machine learning framework for identifying animal diseases, considering the effects of climate change. Because illness dynamics are so complicated and interact with environmental conditions, the method merged image-based deep learning with climate-related data to make predictions more accurate and generalize better. The research utilized a phased development methodology, initiating with a basic Convolutional Neural Network (CNN) exclusively trained on image data, and later integrating additional components such as climatic variables, transfer learning frameworks, and regularization techniques. This study employs a multimodal data fusion approach to accurately assess the influence of climate change on animal disease diagnosis by integrating visual data with climatic textual data. The visual modality comprises animal images used for the identification of disease related symptoms, whereas the climatic modality encompasses numerical and textual representations of environmental data, including temperature and humidity. The image data undergoes processing via deep learning feature extraction networks, including convolutional neural networks (CNNs) and models such as ResNet and YOLOv5. These models acquire advanced visual traits that signify illness patterns, lesions, or atypical physical characteristics. This stage produces a concise feature vector that represents the visual health status of the animal. Simultaneously, the meteorological data, depicted as organized numerical values (e.g., temperature and humidity), are standardized and converted into a feature representation appropriate for machine learning analysis. These climatic characteristics encapsulate environmental stressors that affect illness vulnerability and advancement. The two feature sets are subsequently integrated at the feature level, wherein visual features and climatic features are amalgamated into a cohesive representation. The integrated feature vector is then transmitted to a classification layer or fully connected network that acquires knowledge of the interrelations between visual symptoms and environmental factors. By concurrently learning from multiple modalities, the model can more effectively evaluate illness risk and severity compared to utilizing image data in isolation. The integrated output is utilized to produce diagnostic forecasts, environmental risk assessments, and decision-support suggestions. This multimodal integration enables the system to correlate illness symptoms with climatic conditions, facilitating more precise, climate-informed disease diagnosis and aiding early intervention techniques in livestock.

IV. Results

The results encompass the preparation of both image and climate data, the construction and training of multi-input deep learning models, and the implementation of advanced architectures, including EfficientNetB0. We used training and validation accuracy metrics to evaluate the model, paying close attention to overfitting, model stability, and generalization performance. The suggested method combines traditional CNN-based image classification with environmental data integration and cutting-edge transfer learning. This makes it a complete way to deal with both the problems of finding animal diseases and the growing effects of climate change, as shown in Table I.

TABLE I. THE CNN AND DEEP LEARNING MODELS RESULT

Model Phase	Training Accuracy (%)	Validation Accuracy (%)
Phase 1: CNN (Images Only)	88	65
Phase 2: CNN + Climate Data	88	75
Phase3: EfficientNet0 +Climate Data	92	87
Phase 4: EfficientNet + Regularization	90	91

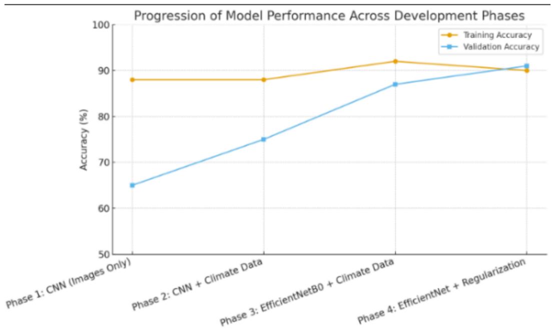

Fig. 1. The progression of accuracy across four phases.

In Fig. 1, the starting point of the CNN that was exclusively trained on image data (Phase 1) was a clear case of overfitting because the training accuracy was about 88%, but the validation accuracy was only about 65%. This revealed that the model couldn't use what it learnt on data that wasn't in the training set. We added climate elements, including temperature and humidity, in Phase 2, which raised the validation accuracy to 75%. The performance of the training remained unchanged. This shows that adding environmental data narrows the gap between training and validation and makes generalization better. We employed EfficientNetB0 for transfer learning in Phase 3, which made both training and validation much more accurate (92% and 87%, respectively). The pre-trained feature extraction layers gave us a strong base, which helped us reach our goal faster and improved the overall prediction performance. Finally, in Phase 4, freezing the pre-trained layers and employing stronger regularization approaches like dropout and L2 regularization made the training and validation performance stay the same. The accuracy of the training data dropped to 90%, but the accuracy of the validation data rose to roughly 91%. This shows that the model is more generic and stable. The final optimized model has a CNN accuracy of more than 90%. Adding climatic data was helpful for making things better. Generalization, transfer learning, and regularization procedures made sure that the model stayed stable and didn't overfit. The link between climate change and animal health shows how important it is to use new diagnostic methods. New vectors and infections appear in areas that were not affected before as temperatures rise, rainfall patterns change, and humidity levels increase. This tendency not only raises the likelihood of outbreaks, but it also makes it harder to manage diseases. Machine learning–based diagnostic tools offer a proactive strategy by facilitating real-time monitoring and early diagnosis, which are crucial for alleviating the impacts of these climate-induced changes. Additionally, connecting illness surveillance systems with climate data can improve early warning systems and help policymakers create targeted policies. The results show that the model's performance has steadily improved from a baseline accuracy of 65% to a higher level by following the previous diagram in the last research, as shown in Fig. 2.

Our second step is a comparative analysis of ResNet, YOLOv5, and AltCLIP methods to get results from different methodologies that we used on the same dataset to check the results compared to the previous one in the training and validation phases.

We start to show the results for three models that were used to make the comparison, starting with the YOLOv5 model.

The training loss for YOLOv5 started at 0.494 and went down to 0.203 by the end of the last epoch. The loss for validation started at 0.528 and went down to 0.426 (Fig. 4). The Top1 Accuracy went up consistently from 78.7% in the first epoch to 85.6% in the last epoch, which shows that the model was learning and performing well on the dataset (Fig. 3).

Then we showed the result, and it's impressive that the algorithm can distinguish between sick and healthy cows. For cows that are lumpy, it gets it right 61% to 83% of the time, and for healthy cows, it gets it right 61% to 99% of the time. The expected probabilities show this difference even more clearly: the confidence ratings for healthy cows are between 0.17 and 0.99, whereas those for lumpy cows are between 0.13 and 0.83. But since the chances are about 0.5 for both (Fig. 6).

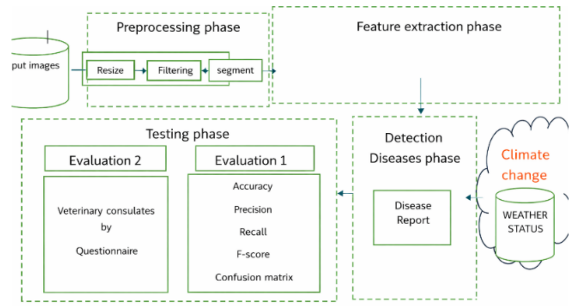

Fig. 2. Block diagram for the prediction of disease in animals [1].

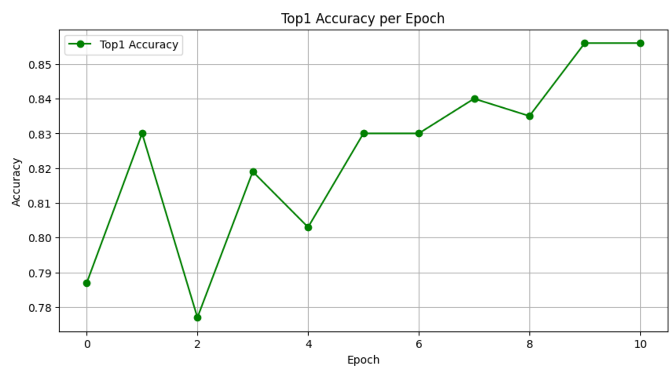

Fig. 3. The accuracy per epoch for YOLOv5.

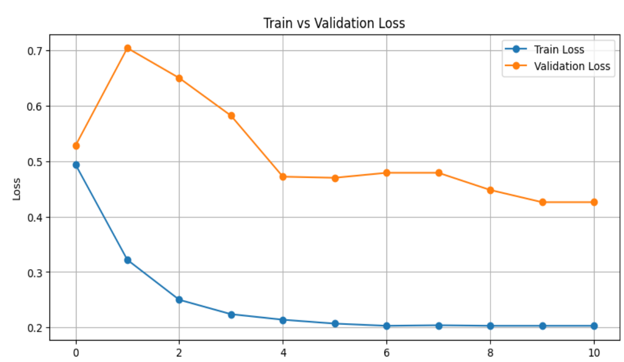

Fig. 4. The train and validation loss results for YOLOv5.

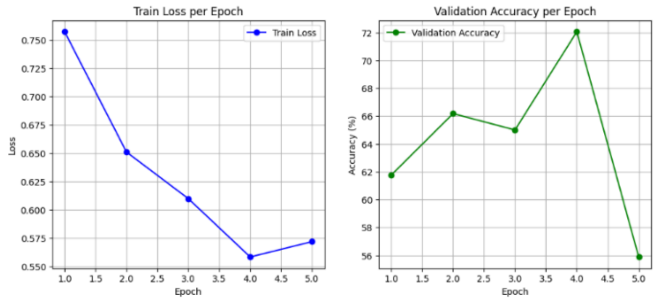

Fig. 5. The train and validation results for ResNet.

The training loss for ResNet went from 0.7572 to 0.5586 during five epochs, which shows that it was learning well. The validation accuracy began at 61.76%, increased to 96.18% in the second epoch, and thereafter decreased to 55.88%. This suggests that ResNet can be quite precise at some stages during training (Fig. 5).

The dataset was carefully prepared using an 80/20 train-validation split, ensuring proper shuffling and organization for balanced learning. Over the course of 10 training epochs, the model achieved a final Top 1 accuracy of 85%, with the training loss reduced to 0.2 and validation loss to 0.3. The small loss gap of 0.1 indicates strong generalization and minimal signs of overfitting. Analysis suggests that the optimal stopping point was around Epoch 8, where performance stabilized. Overall, the model trained successfully, demonstrating reliable accuracy and robustness, making it well-suited for final testing and deployment.

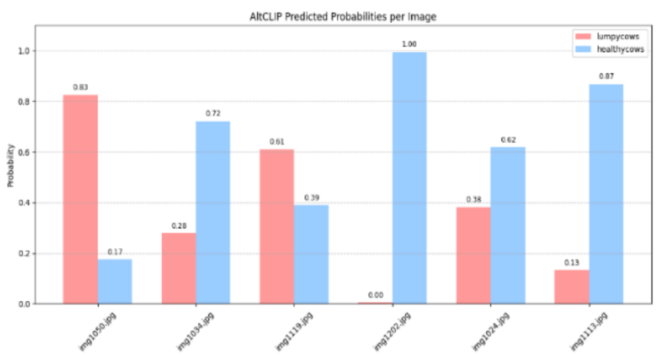

Fig. 6. The training and validation for ResNet results.

Groups, the model doesn't know what to do with more unclear photographs. Even with these issues, the model has gotten better at generalizing across different samples because of data augmentation techniques, including rotation, random flipping, and scaling. Future improvements could include adding more data to the dataset and employing fine-tuning methods to make class separation better and reduce confusion. This would make the performance better and more stable. Table II shows all the outcomes of the comparisons.

Interventions. While promising, this approach requires continued investment in data collection, model refinement, and interdisciplinary collaboration between veterinarians, climate scientists, and computer engineers to maximize its impact. At the end, we show the total result in Fig. 7.

TABLE II. THE COMPARISON OF THE MODELS' RESULTS

Model	Training Loss Trend	Validation Loss / Accuracy	Key Results	Strengths
YOLOv5	Decreased from 0.494 → 0.203	Validation loss 0.528 → 0.426; Top-1 Accuracy improved from 78.7% → 85.6%	Stable and consistent improvement	Reliable performance across epochs; best for general classification & detection
ResNet	Decreased from 0.7572 → 0.5586 (5 epochs)	Validation accuracy started 61.76%, peaked at 96.18%, fluctuated between 65–72%, ended at 55.88%	Can reach very high accuracy at certain stages	Strong peak accuracy, but unstable validation results
AltCLIP	N/A (probability-based output)	Provides per-class probabilities (e.g., 0.825 lumpycows, 0.996 healthycows, 0.721–0.868 for other images)	High confidence and precise predictions	Best for detailed per-image classification and semantic discrimination

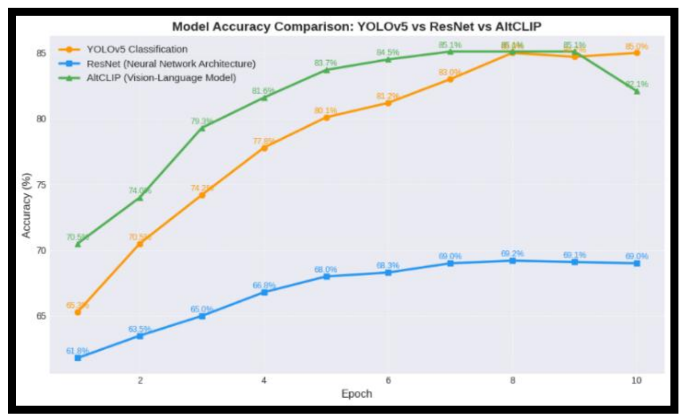

Fig. 7. The accuracy comparison between the models.

In the last step, we use the best result of models to the GUI, which was also built to merge visual and environmental data so that diseases might be found on their own. The trained models in the system use weather data and pictures of animals to make an environmental interpretation, a combined stress index, a quantitative risk score (0–100), and suggestions for what to do next, like getting immediate veterinary care, keeping an eye on the animal often, or making sure it is healthy. This combination approach shows that using climate-sensitive analysis with deep learning architectures may make diagnoses far more accurate, let doctors make proactive choices, and allow for ecological.

V. Graphical User Interface (GUI) for Climate-Aware Animal Disease Diagnosis

To turn the complex parts of the proposed machine learning architecture into an app that is easy to use and accessible, it is important to make a graphical user interface (GUI). Its main purpose is to make it easier to enter, process, and understand data, which will make the system more useful and applicable in real-life weather data that is important, such as temperature and humidity. After the inputs are sent in, the interface automatically runs them through the learnt classification models, which gives very detailed diagnostic results. These include a combined stress index, descriptions of the environment, graphs showing how likely an illness is to happen, and a risk score that can be measured and goes from zero to one hundred. GUI also gives simple suggestions depending on the diagnostic results, including getting immediate veterinary attention, keeping an eye on the situation regularly, or confirming that the animal is healthy. We take a photo and send it to the system. The pic shown below is an example of upload in the system, using two climate change temperature and humidity, and the shape of the GUI for the system, as shown in Fig. 8.

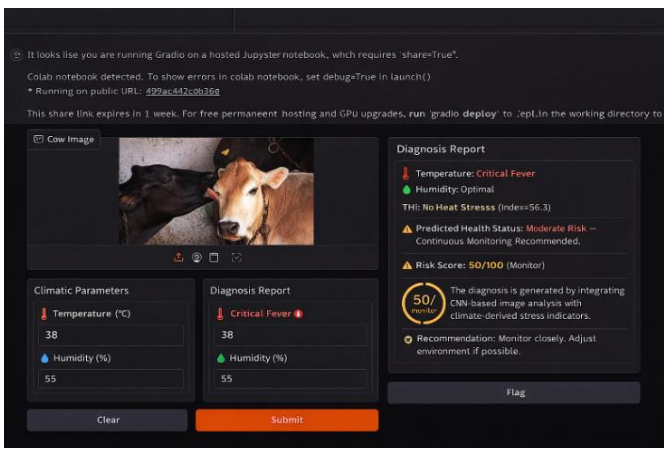

Fig. 8. The GUI and the result after uploading the picture.

The GUI that was built uses animal picture processing and environmental data (temperature = 33 °C, humidity = 60%) to automatically discover diseases. The system used the model YOLOv5 to find hypothermia at the right humidity and a THI of 28.9, which suggests there was no heat stress. The diagnosis assigned the case a risk score of 50 out of 100 and indicated it "Needs Monitoring". This suggested that the person should be followed attentively, and the environment should be modified. This shows how the system could keep an eye on animal health by using AI-based detection and climate evaluation together.

VI. Discussion

This study's findings illustrate the efficacy of combining machine learning methods with climatic data to improve the diagnosis of animal diseases amid shifting environmental conditions. The noted enhancement in diagnostic precision corroborates the concept that climate variability, especially variations in temperature and humidity, significantly influences the onset and development of bovine illnesses. By integrating these environmental aspects into the diagnostic framework, the proposed model offers a more thorough comprehension of disease dynamics than image-based analysis alone. The utilization of convolutional neural networks, in conjunction with sophisticated classification models like ResNet, YOLOv5, and AltCLIP, facilitated effective feature extraction and dependable disease classification. These models proficiently differentiated between healthy and unhealthy animals, even in visually intricate situations, illustrating their appropriateness for veterinary diagnostic applications. The findings demonstrate that transfer learning and multimodal designs enhance generalization and decrease misclassification, especially in instances where disease symptoms are mild or overlapping. The incorporation of climate factors with ocular illness detection markedly improved the system's prediction performance. The integrated analysis enabled the model to evaluate environmental stressors and correlate them with disease risk, providing significant insights into the impact of climate change on livestock health. This method enhances early disease identification and facilitates proactive risk assessment and climate adaptation measures in cattle management. The creation of a graphical user interface (GUI) enhances the practical utility of the proposed technology. GUI facilitates the connection between intricate machine learning models and end users, including farmers and veterinarians, by displaying diagnostic results, environmental risk assessments, and practical advice in an easily understandable style. This promotes informed decision-making, allowing for prompt actions that can mitigate disease transmission, lessen economic losses, and enhance animal welfare. Notwithstanding these encouraging outcomes, specific limits must be recognized. The model's effectiveness is contingent upon the quality and diversity of the training data, whereas discrepancies in picture quality or insufficient climatic records may influence diagnostic precision. Subsequent research may rectify these limitations by integrating larger, multi-regional datasets, supplementary environmental factors, and real-time sensor data to augment robustness and scalability. This study underscores the capacity of climate-conscious machine learning frameworks to revolutionize animal disease detection. The suggested method integrates visual analysis with environmental context, enhancing sustainable livestock management and providing a crucial tool for alleviating the increasing health concerns linked to climate change.

VII. Conclusion

Climate change is making animal diseases spread faster, and outbreaks happen more often, are worse, and are affecting more animals. These changes pose a major threat to the stability of agricultural economies around the world, food safety, and animal health. Standard diagnostic methods are useful, but they might not be useful in all cases because they cost a lot, take a long time, and aren't very scalable. This makes them less useful for keeping an eye on diseases in real-time over a wide area in a world that is changing quickly. This study presents a sophisticated diagnostic system that utilizes image-based data to rapidly and accurately identify animal diseases through cutting-edge machine learning and deep learning techniques. The suggested method combines convolutional neural networks (CNNs) with several strong classification architectures, such as ResNet, YOLOv5, and AltCLIP, to make feature extraction, localization, and visual-semantic comprehension better. The method enhances early diagnosis by integrating diagnostic predictions with environmental factors such as temperature and humidity.

VIII. Future Directions

There are several interesting avenues for this field's research. First, the robustness and generalizability of CNN-based diagnostic models will be enhanced by enlarging datasets to encompass a greater variety of animal species, illnesses, and climates. Second, the accuracy of disease prediction and outbreak forecasting can be improved by combining multi-modal data, including sensor data (e.g., temperature, humidity, and movement tracking), farm management techniques, and satellite-based climate information. Farmers in rural or resource-poor areas might also benefit from real-time diagnostic tools that don't need expensive infrastructure. They could do this by making lightweight AI models that work well on mobile or edge devices. Future research may also examine explainable AI (XAI) methodologies to enhance the transparency and dependability of model decisions, hence facilitating informed decision-making by policymakers and veterinarians. Finally, creating worldwide data-sharing platforms that connect animal health records and weather trends will make it easier to keep an eye on huge areas, help create early warning systems, and help design agricultural systems that can handle climate change.

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