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AI-Driven Disease Diagnosis in Falcons Using Machine Learning

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Abstract: Falcons are highly prized avian species, particularly in regions where falconry is an important cultural and economic activity. Ensuring their health and detecting diseases at an early stage is crucial, yet traditional veterinary diagnosis can often be delayed due to limited accessibility to expert care. To address this gap, we present Falcon Doctor, an AI-powered, web-based intelligent system designed to predict falcon diseases based on observable symptoms using machine learning algorithms. The system enables users to select symptoms through an intuitive user interface and leverages a trained Random Forest model to predict the most probable disease from a set of ten common falcon diseases.

The prediction module was developed and evaluated using a dataset of symptom-disease combinations sourced from a reputed falcon care centre. To ensure accuracy and reliability, the system compares the performance of two classification models—Random Forest and Naïve Bayes—by analysing their evaluation metrics such as accuracy, precision, recall, and F1-score. Based on the comparative results, Random Forest provided superior prediction capability and was selected as the final model for integration.

In addition to disease detection, Falcon Doctor includes a chatbot module powered by Gemini AI, enabling users to ask natural language queries regarding symptoms, treatments, preventive measures, and care routines. Moreover, the system provides a hospital locator feature, allowing users to find nearby veterinary clinics specialized in avian medicine.

An admin panel is integrated into the platform for managing users, hospitals, and feedback, ensuring streamlined backend operations. The overall goal of Falcon Doctor is to make falcon disease diagnosis more accessible, faster, and efficient, supporting bird conservation efforts and reducing dependency on immediate physical consultations. Future enhancements aim to include real-time vet consultations, broader disease coverage, and intelligent chatbot improvements to elevate the quality of digital avian healthcare.

Keywords: Machine Learning, Random Forest, Falcon Disease Detection, Veterinary Assistance, AI Chatbot, Symptom-Based Diagnosis, Web Application, Gemini AI.

I. INTRODUCTION

Falcons are one of the most respected and valuable birds in many parts of the world, especially in regions where falconry is considered a cultural tradition.The Peregrine Falcon , one of the fastest birds in the world, is also found across various regions of India, especially during the winter months as a migratory visitor. Figure. 1 shows the Peregrine Falcon as an example, commonly seen in the Indian subcontinent. Due to their delicate health and high economic and emotional value, maintaining their wellness becomes essential. In many cases, falcon owners and handlers are unable to detect diseases at an early stage due to a lack of veterinary knowledge or unavailability of professional support. Traditional diagnosis methods require expert veterinarians and laboratory tests, which may not be easily accessible in remote areas or in emergency situations. To overcome these challenges, we propose a system named Falcon Doctor, an AI-based web application designed for predicting falcon diseases based on the symptoms selected by the user. The system is trained using machine learning algorithms to classify and detect the most probable disease among ten common falcon diseases. A dataset containing combinations of symptoms and diseases was used to train and test the models. The model also provides additional information about the predicted disease such as an overview, mode of transmission, preventive measures, control methods, and alerts. The system is developed with a user-friendly interface that allows users to select symptoms easily through checkboxes. Upon submission, the system processes the input and displays the disease with the highest probability using a trained Random Forest model. For comparison and validation, the model performance was also evaluated against the Naïve Bayes classifier using metrics like accuracy, precision, recall, and F1-score. Based on the results, the Random Forest model achieved higher accuracy and was selected as the final prediction model for deployment.

Apart from disease detection, Falcon Doctor includes additional features such as a Gemini-powered chatbot that assists users by answering questions related to falcon health, treatments, and care through natural language interaction. The system also provides a hospital locator that helps users identify nearby veterinary clinics specializing in avian medicine. An admin panel is included to manage users, hospitals, and feedback efficiently. This project aims to make disease detection more accessible, improve the quality of care for falcons, and assist users in taking timely actions.

Falcons, like other birds of prey, are susceptible to a variety of diseases that can severely impact their health and performance. The most common diseases affecting falcons include Avian Influenza, Aspergillosis, Coccidiosis, Trichomoniasis, Newcastle Disease, Bumblefoot, Uropygial gland issues. These diseases manifest through a range of symptoms such as respiratory distress, weight loss, lethargy, diarrhoea and abnormal droppings, making diagnosis challenging due to the overlap of clinical signs.

Many of these infections, particularly Aspergillosis and Avian Influenza can become life-threatening if not detected early. In falconry, where performance and conditioning are vital, such health issues can result in reduced activity or permanent impairment. Additionally, some of these diseases are zoonotic, posing health risks to humans who handle the birds. Therefore, early detection and intervention play a crucial role in preventing complications, reducing mortality, and ensuring the well-being of both the falcons and their handlers.

Traditionally, falcon diseases are diagnosed through manual observation and laboratory tests, which require skilled veterinarians and are not always accessible. This highlights the importance of an automated system like Falcon Doctor that enables symptom-based disease prediction using machine learning, thus aiding falconers and avian caretakers in managing health risks effectively.

Fig. 1 Peregrine Falcon

II. LITERATURE REVIEW

The application of artificial intelligence in veterinary diagnostics has seen substantial growth, particularly in species where traditional diagnostic infrastructure is limited. Earlier research [1] introduced a symptom-based cattle disease prediction system utilizing classifiers like Naïve Bayes and Decision Trees, demonstrating that machine learning could significantly enhance early detection of diseases. Similarly, [2] explored mobile technology for poultry disease diagnosis through a combination of symptom selection and image input. However, these systems were tailored for livestock and lacked advanced features like probability-based ranking and disease-specific content. In a more technical approach, [3] compared various models including Random Forest and KNN for pet disease prediction, concluding that Random Forest provided better accuracy and robustness in noisy datasets — a key insight that supports its adoption in the Falcon Doctor system.

Simultaneously, chatbots have been investigated as virtual helpers in the veterinary field [4] proposed a rule-based veterinary chatbot for pet guidance, but its limited NLP capabilities and scalability restricted its effectiveness. This was addressed in Falcon Doctor by integrating Google's Gemini for general conversational AI support. A contextual survey by [5] highlighted the need for specialized digital health systems for falcons, especially in regions where falconry is culturally vital, urging for tools that offer early diagnosis through intelligent systems.

A foundational study [6] provides a comprehensive overview of the common diseases affecting falcons, including viral, bacterial, fungal, protozoan, and parasitic infections. Conducted across multiple falcon hospitals and breeding centers in the UAE between 2011 and 2015, the research highlights that while many falcon diseases are treatable if identified early, effective prevention requires proper hygiene, balanced nutrition, and regular veterinary check-ups. The study emphasizes that most bacterial and viral diseases are contracted through infected prey and that ectoparasites such as mites, lice, and ticks are prevalent.

More recently, [7] introduced a deep learning-based framework which represents a significant advancement in falcon-specific diagnostics. Their system uses endoscopic imagery to classify diseases like Liver Disease and Aspergillosis through a hybrid deep learning architecture that combines ConvNeXt and EfficientNet models.

Achieving a training accuracy of 99.65% and validation accuracy of 98.50%, their approach outperforms individual CNNs by leveraging fused feature extraction, demonstrating high potential for image-based classification in veterinary AI. However, while their model excels in image-based clinical contexts, it lacks user-interaction capabilities, hospital locators, and symptom-based prediction, which are core features of Falcon Doctor. Thus, this research advances diagnostic precision via deep learning, the Falcon Doctor project offers a broader, more accessible solution that bridges both expert and layperson needs through user-friendly interfaces, symptom input, probabilistic prediction, and chatbot assistance.

A thorough review of existing literature and technologies revealed that while digital health tools are increasingly popular in human and domestic animal healthcare, their application in avian species, particularly falcons, remains sparse. Existing models rely heavily on rule-based systems or simple classifiers, which do not perform well on non-linear, high-dimensional medical data.

Recent advances in machine learning have shown great potential for use in biomedical applications, especially when it comes to ensemble techniques like Random Forest. Studies have demonstrated that such models handle large feature sets efficiently and provide high prediction accuracy even with noisy or missing data. However, these technologies are rarely adapted to bird health, let alone specifically for falcons. This project fills that niche by adapting machine learning models to a well-curated falcon disease dataset and integrating it into a dynamic, accessible web interface.

III. PROPOSED SYSTEM

The proposed Falcon Doctor system is a comprehensive digital health platform designed specifically for the early detection and management of falcon diseases. It combines machine learning, geolocation technology, and AI-driven conversational tools within a robust web framework to serve both falcon owners and veterinary professionals. The system is designed with a focus on accuracy, accessibility, and usability, making it a viable tool in regions where falconry is prevalent and falcon health is a top priority.Figure 2 illustrates the block diagram of the proposed Falcon Doctor system, outlining the key components such as user input, symptom processing, disease prediction using the Random Forest model.

A. Symptom-Based Disease Prediction

At the core of Falcon Doctor lies the disease prediction engine powered by a Random Forest classification model. This model is trained on a curated dataset of 11 falcon diseases, each characterized by a unique set of 10 to 15 symptoms. Users interact with this module through an intuitive interface where they can select observed symptoms using checkboxes. Once the symptoms are submitted, the backend processes the input and feeds it to the machine learning model, which returns a single disease prediction with the highest probability score.

Random Forest's resistance to overfitting and capacity to handle multiclass classification issues make it an especially useful tool. The model also maintains high accuracy despite noise or slight inconsistencies in symptom selection, making it reliable even when used by non-experts.

B. Interactive Chatbot Using Gemini

To complement the diagnostic process, the Falcon Doctor platform integrates a chatbot powered by the Gemini conversational AI. The chatbot acts as a virtual assistant that can:

- Clarify disease symptoms and names
- Explain transmission modes and prevention techniques
- Guide users through general falcon care
- Provide educational insights on falconry practices and veterinary ethics

This interactive tool allows users to ask questions in natural language and receive intelligent, context-aware responses, making the system accessible to individuals with varying degrees of technical or veterinary knowledge.

C. *Hospital Locator Module*

A key feature of Falcon Doctor is its location-based hospital locator tool. This module utilizes geolocation APIs (such as Google Maps API or similar services) to detect the user's current location and display a list of nearby falcon-specific veterinary centres. Each listing provides essential details such as hospital name, contact number, distance from the user, and directions via mapping tools. This functionality ensures that users can transition from diagnosis to real-world treatment quickly, effectively closing the loop between problem identification and resolution.

D. Admin and User Panels

The system differentiates between two types of users—administrators and general users—each provided with custom functionalities:

- Admin Portal: Designed for system managers and veterinary professionals, the admin panel allows secure login, management of hospital and disease databases, viewing of user feedback, and monitoring system usage. Admins can add or remove hospitals, update disease information, and track how the system is being used.
- User Portal: Designed for falconers, pet owners, or general users, the user panel offers features like registration/login, symptom submission, chatbot interaction, hospital lookup, and feedback submission. The interface is simple, responsive, and optimized for various devices.

By separating roles, the system maintains data integrity, access control, and workflow management, which is crucial in multi-user environments.

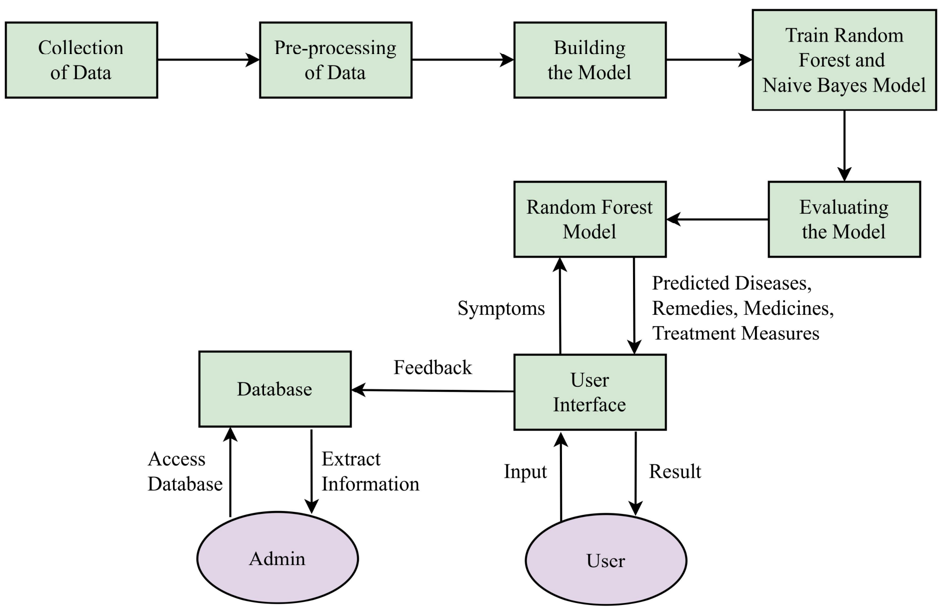

Fig. 2 Block Diagram

IV. METHODOLOGY

The methodology used to build the Falcon Doctor system combines machine learning techniques with a user-friendly web interface. The goal is to provide an intelligent platform that predicts diseases in falcons based on symptoms provided by users. The methodology is designed to ensure that the system can deliver timely, accurate predictions while being scalable and accessible to a wide range of users, from falconers to veterinarians. The system development process is broken down in depth below.

A. Data Collection and Preprocessing

The first step in developing the Falcon Doctor system is the collection and preparation of data. The quality of the dataset directly influences the performance of the disease prediction model. In this project, we used a dataset of 11 falcon diseases, each associated with 10–15 symptoms. These symptoms were carefully curated from falcon health experts, veterinarians, and online medical resources.Figure 3 shows a snapshot of the dataset used for training and testing the machine learning models, containing symptom combinations mapped to corresponding falcon diseases.

- Data Collection: The dataset contains records of falcon diseases, with each record associated with symptoms, disease name, and additional information relevant to diagnosis. This data is gathered from a combination of expert falcon care sources, veterinary documentation, and medical journals.
- Data Preprocessing: The dataset undergoes cleaning, transformation, and feature selection to ensure the input data is suitable for training the machine learning models. Missing data is handled, categorical features are encoded, and numerical data is normalized for consistency.

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	A	B
1	Condition	Symptoms
2	Capillaria	diarrhea, weight loss, anorexia, dull appearance, dehydration
3	Capillaria	anorexia, lethargy, swelling in the digestive tract
4	Lead Poisoning	lethargy, difficulty flying, uncoordinated movement, depression
5	Capillaria	weight loss, dull appearance, dehydration, swelling in the digestive tract
6	Uropygial Gland Issues	swelling at the base of the tail, feather loss, scabbing
7	Lung Worms– Serratospiculum spp.	weight loss, decreased activity
8	Capillaria	diarrhea, anorexia, dull appearance, anemia, dehydration
9	Coccidiosis	weight loss, dehydration, loss of coordination, drooping wings, pale combs
10	Coccidiosis	diarrhea (sometimes bloody), lethargy, decreased appetite, dehydration, pale combs
11	Lead Poisoning	lethargy, vomiting, seizures, green feces, difficulty flying, head tremors, uncoordinated movement, depression
12	Lead Poisoning	lethargy, green feces, difficulty flying, uncoordinated movement
13	Aspergillosis	weight loss, nasal discharge, open-mouth breathing
14	Lead Poisoning	weight loss, vomiting, difficulty flying, depression, loss of appetite
15	Newcastle Disease (Epilepsy)	muscle tremors, diarrhea
16	Bumblefoot	swelling and redness on the feet, lameness or reluctance to perch, scabbing or ulcers on footpads, heat or pain in the affected area, decreased activity
17	Aspergillosis	weight loss, lethargy, coughing, open-mouth breathing
18	Bumblefoot	swelling and redness on the feet, scabbing or ulcers on footpads, heat or pain in the affected area, changes in posture, abscess formation, decreased activity
19	Bumblefoot	swelling and redness on the feet, scabbing or ulcers on footpads, abscess formation
20	Trichomoniasis	yellowish lesions in the mouth/throat, lethargy, vomiting, drooling, poor feather quality
21	Newcastle Disease (Epilepsy)	twisting of the neck, seizures, respiratory distress, coughing, diarrhea, drooping wings
22	Bumblefoot	swelling and redness on the feet, lameness or reluctance to perch, heat or pain in the affected area
23	Lung Worms– Serratospiculum spp.	difficulty breathing, decreased activity, gasping for air, open-mouth breathing, regurgitation, loss of appetite, lethargy
24	Lung Worms– Serratospiculum spp.	coughing, difficulty breathing, decreased activity, open-mouth breathing
25	Lead Poisoning	lethargy, seizures, head tremors, depression
26	Coccidiosis	diarrhea (sometimes bloody), weight loss, ruffled feathers, dehydration
27	Capillaria	diarrhea, weight loss, anorexia, dull appearance, lethargy, dehydration, swelling in the digestive tract

Fig. 3. Dataset Snapshot

B. *Model Training*

Training the model comes next after the data is ready. The Random Forest classifier is chosen for this task due to its ability to handle high-dimensional, non-linear data, and its robustness against overfitting.

Algorithm: Random Forest Training:

1) Input: Pre-processed dataset with symptom data (features) and corresponding disease labels (targets).
2) Step 1: First, divide the data into sets for testing and training:
   - Split the dataset into two parts: 20% for testing and 80% for training.
   - Perform stratified sampling to maintain the distribution of diseases in both sets.
3) Step 2: Initialize Random Forest Classifier:
   - Establish the Random Forest model with the following hyperparameters:
     - n_estimators: The number of trees in the forest is estimated to be at least 100.
     - max_depth: The maximum depth of each decision tree (to avoid overfitting).
     - min_samples_split: Minimum number of samples required to split an internal node (default is usually 2).
     - random_state: Ensures reproducibility of results.
4) Step 3: Train the Model:
   - Use the fit() method to train the Random Forest model on the training data. This involves constructing multiple decision trees, each trained on a random subset of features and samples.
   - Each tree in the forest makes an independent prediction, and the Random Forest algorithm aggregates the predictions (majority vote for classification) to provide the final result.
5) Step 4: Model Evaluation:
   - Evaluate the trained model using the testing set to assess its performance.
   - Compute the accuracy, precision, recall, F1-score, and confusion matrix to evaluate the model's performance on unseen data.
   - Perform cross-validation (e.g., k-fold cross-validation) to verify the robustness of the model.
6) Step 5: Model Tuning (Optional):
   - Use techniques like Grid Search or Randomized Search to fine-tune hyperparameters and improve model performance.
   - Adjust parameters such as n_estimators, max_depth, and min_samples_split to achieve the best balance between bias and variance.
7) Output: A trained Random Forest model capable of predicting diseases based on user-selected symptoms.

C. *Disease Prediction*

Once the model is trained, it can be integrated into the Falcon Doctor system to predict diseases based on user inputs. When a user selects symptoms, the system uses the trained model to predict the most likely disease.Figure 4 displays the symptom selection page of the Falcon Doctor system, where users can choose observed symptoms through a checkbox-based interface. Figure 5 illustrates the predicted disease page, which presents the most probable falcon disease along with detailed information based on the selected symptoms.

- User Inputs Symptoms: The user selects symptoms from a predefined list in the system interface.
- Prediction Process: The system processes these symptoms through the trained Random Forest model to predict the disease with the highest probability.
- Display of Results: The system shows the predicted disease, its image, an overview, transmission details, prevention measures, and relevant alerts.

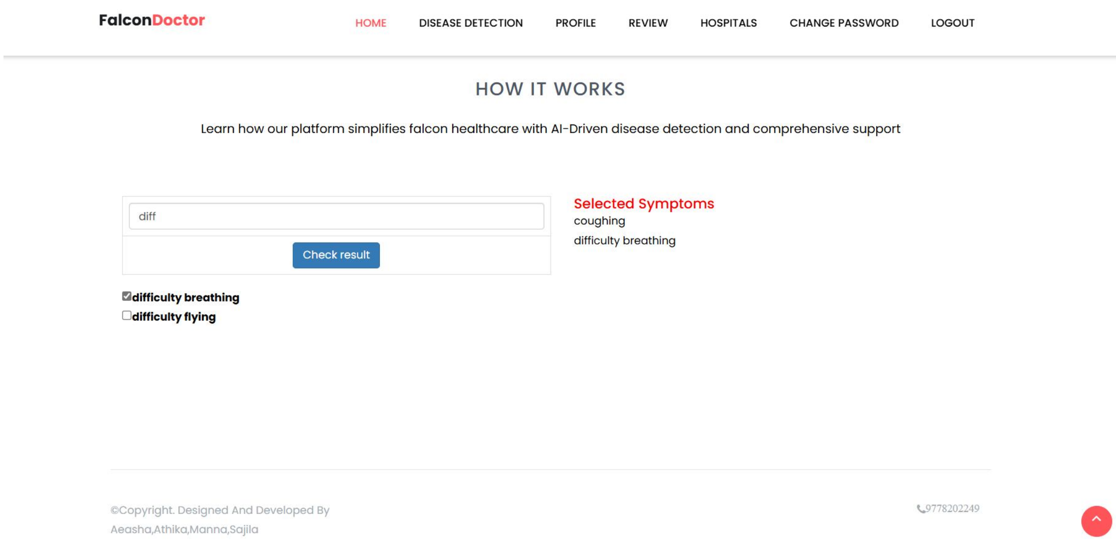

Fig. 4 Symptom Selection

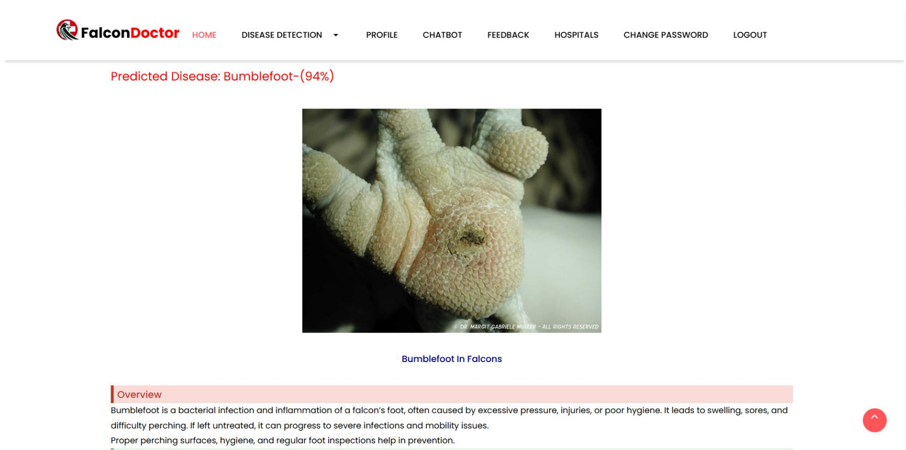

Fig. 5 Predicted Disease

D. System Integration and User Interaction

The Falcon Doctor system integrates the disease prediction model with a web interface built on Django. This integration ensures that users can easily interact with the system to predict diseases and access additional information.

- User Registration/Login: New users can register and existing users can log in to access the disease prediction feature.
- Symptom Selection: Users can select symptoms through checkboxes, which trigger the disease prediction process.
- Chatbot Interaction: The system includes a chatbot powered by Gemini, which provides users with relevant information about diseases, prevention, and general falcon care.
- Hospital Locator: The system uses geolocation to help users locate nearby veterinary clinics specializing in falcon care.
- Prediction Results: The user is presented with the predicted disease along with associated details and an option to locate nearby hospitals.

V. IMPLEMENTATION

The Falcon Doctor system was developed to predict diseases in falcons based on their symptoms. The system uses machine learning algorithms, integrated into a web-based platform. The implementation consists of backend development, machine learning model integration, and web application features.

A. Backend Development (Django Framework)

The Django web framework, which offers a stable and expandable platform for web application development, is used to construct the system's backend. The system follows the Model-View-Template (MVT) architecture.

1) Models:
    - User Model: Captures user details such as name, email, phone number, gender, and password.
    - Disease Model: Stores information on diseases, including disease names, symptoms, and details like transmission, prevention, and control.
    - Hospital Model: Contains data on available falcon hospitals or clinics, including location and contact information.
    - Feedback Model: Stores user feedback, allowing users to rate and comment on the system's predictions and functionality.
2) Views:
    - Views manage logic for user interactions, including receiving symptom inputs and returning disease predictions.
3) Templates:
    - Templates define the structure of the web pages. They include forms for symptom input, disease prediction results, hospital locations, and chatbot interaction.

B. Machine Learning Model Implementation

The disease prediction is powered by machine learning, with Random Forest and Naïve Bayes classifiers being tested. Ultimately, Random Forest was selected due to its superior performance.

1) Dataset Preparation:
    - The dataset consists of 10 diseases, each associated with 10 to 15 symptoms. The data was cleaned, missing values were imputed, and categorical variables were encoded for model compatibility.
2) Data Preprocessing:
    - Features were encoded using label encoding for categorical variables. An 80-20 split was used to separate the dataset into training and test sets.
3) Model Training:
    - The Random Forest model was trained using Scikit-learn with 100 trees, a typical configuration for robust performance.
    - Hyperparameters such as max_depth and n_estimators were tuned using GridSearchCV to optimize model performance.
4) Model Evaluation:
5) The model was evaluated using metrics such as accuracy, precision, recall, and F1 score. These metrics made it easier to compare Random Forest's performance to that of Naïve Bayes, demonstrating that Random Forest offered higher accuracy.
6) Disease Prediction:
    - Users submit their symptoms through a form on the web application. The trained Random Forest model predicts the disease with the highest probability based on the symptom combination.
7) Probability Calculation:
    - For each input, the Random Forest model aggregates predictions from individual trees. The final prediction is based on the majority vote, with the probability score representing the fraction of trees that predicted the same disease.

C. Web Application Integration

The web application includes several key features:

1) Disease Detection Interface:
    - Users can select symptoms from a list of checkboxes. Upon submission, the system uses the machine learning model to predict the disease and displays the result, including additional details such as the disease overview, transmission, prevention, and control measures.

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2) Hospital Locator:
   - Using Google map API, the system provides an interactive map for users to locate nearby falcon hospitals or clinics.

3) Chatbot:
   - The chatbot, powered by Google Gemini, offers real-time support, answering user queries about diseases, treatments, and general system navigation.

VI. RESULTS AND DISCUSSION

The Falcon Doctor system was rigorously evaluated to assess the performance of its disease prediction capabilities and overall system functionality. The system leverages machine learning models, specifically Random Forest and Naïve Bayes, for predicting falcon diseases based on selected symptoms. This section presents the evaluation results and provides an in-depth discussion regarding the model's performance, including the confusion matrix, ROC curve, and model comparisons.

A. Model Evaluation Results

To determine the optimal model for disease prediction, we compared the performance of the Random Forest and Naïve Bayes classifiers. The models were trained using a dataset consisting of 10 diseases, each associated with 10-15 symptoms. The evaluation metrics used for model comparison include accuracy, precision, recall, F1 score, confusion matrix, and ROC curve.

1) Accuracy and Evaluation Metrics

The following metrics were used to assess the Random Forest and Naïve Bayes models:

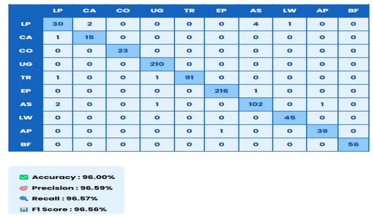
- Accuracy: The The percentage of accurate predictions the model generates.
  - Random Forest: 98.70%
  - Naïve Bayes: 96.00%
- Precision: The model's capacity to forecast just the appropriate instances.
  - Random Forest: 96.91%
  - Naïve Bayes: 96.59%
- Recall: The model's capacity to accurately identify every positive case.
  - Random Forest: 96.67%
  - Naïve Bayes: 96.57%
- F1 Score: The precision and recall harmonic means.
  - Random Forest: 97.69%
  - Naïve Bayes: 96.56%

From these results, Random Forest clearly outperforms Naïve Bayes in all key metrics, making it the ideal choice for disease prediction in falcons.

2) Confusion Matrix

The Confusion Matrix is a crucial tool for assessing the performance of classification modelsIt offers information about the kinds of mistakes the model makes. The confusion matrix for both models is presented below:

The Random Forest model shows that the majority of predictions are correct, with few misclassifications (indicating a low number of false positives and false negatives). While Naïve Bayes performs reasonably well, it has a higher number of misclassifications compared to Random Forest, particularly in diseases with complex symptom combinations. Figure 6 shows the confusion matrix for the Naïve Bayes classifier, representing the model's performance in predicting falcon diseases based on the test dataset. Figure 7 presents the confusion matrix for the Random Forest classifier, highlighting its improved accuracy and robustness compared to Naïve Bayes in classifying falcon diseases.


Confusion Matrix For Naive Bayes Classifier

	LP	CA	CO	UG	TR	EP	AS	LW	AP	BF
LP	30	2	0	0	0	0	4	1	0	0
CA	1	15	0	0	0	0	0	0	0	0
CO	0	0	23	0	0	0	0	0	0	0
UG	0	0	0	210	0	0	0	0	0	0
TR	1	0	0	1	91	0	0	0	0	0
EP	0	0	0	0	0	216	1	0	0	0
AS	2	0	0	1	0	0	102	0	1	0
LW	0	0	0	0	0	0	0	45	0	0
AP	0	0	0	0	0	1	0	0	39	0
BF	0	0	0	0	0	0	0	0	0	56

Accuracy : 96.00%
Precision : 96.59%
Recall : 96.57%
F1 Score : 96.56%

Fig. 6 Confusion Matrix for Naïve Bayes Classifier

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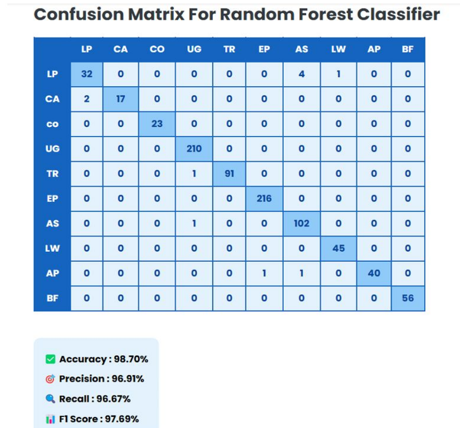

Confusion Matrix For Random Forest Classifier

	LP	CA	CO	UG	TR	EP	AS	LW	AP	BF
LP	32	0	0	0	0	0	4	1	0	0
CA	2	17	0	0	0	0	0	0	0	0
co	0	0	23	0	0	0	0	0	0	0
UG	0	0	0	210	0	0	0	0	0	0
TR	0	0	0	1	91	0	0	0	0	0
EP	0	0	0	0	0	216	0	0	0	0
AS	0	0	0	1	0	0	102	0	0	0
LW	0	0	0	0	0	0	0	45	0	0
AP	0	0	0	0	0	1	1	0	40	0
BF	0	0	0	0	0	0	0	0	0	56

Accuracy : 98.70%
Precision : 96.91%
Recall : 96.67%
F1 Score : 97.69%

Fig. 7 Confusion Matrix for Random Forest Classifier

3) ROC Curve (Receiver Operating Characteristic Curve)

The ROC Curve is another important evaluation tool used to measure the performance of binary classifiers. For various thresholds, it shows the trade-off between the false positive rate (1-specificity) and the actual positive rate (sensitivity).

- Random Forest ROC Curve:
  - The Random Forest ROC Curve is nearer the upper-left corner, suggesting a low false positive rate and a high true positive rate. This suggests that Random Forest has a strong ability to correctly classify positive instances (correct disease predictions).
- Naïve Bayes ROC Curve:
  - The ROC Curve for Naïve Bayes is further from the top-left corner compared to Random Forest, indicating a slightly lower true positive rate and higher false positive rate.
  - AUC (Area Under Curve):
    - Random Forest: 0.97
    - Naïve Bayes: 0.96

The AUC for Random Forest is significantly higher, further confirming that Random Forest is more effective in distinguishing between diseases with different symptom patterns.Figure 8 displays the ROC curve, illustrating the trade-off between the true positive rate and false positive rate for the classifiers used in falcon disease prediction.

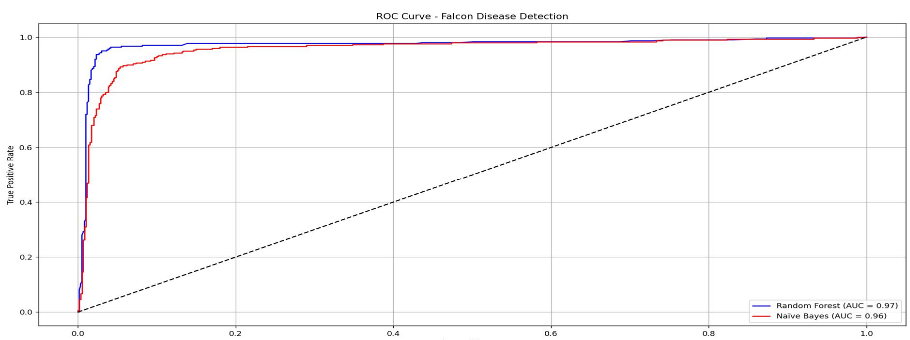

Fig. 8. ROC Curve

B. System Performance and Response Time

The Falcon Doctor system was also evaluated in terms of response time and user experience:

1) Disease Prediction Time:

- The system predicts diseases in under 5 seconds for a typical input of symptoms. This ensures a responsive and efficient user experience, allowing real-time predictions for falcon diseases.

2) User Interface:

- The user interface is clean, intuitive, and easy to navigate. The disease detection page provides a simple checkbox interface for users to select symptoms. Upon submission, the prediction, along with details such as disease overview, prevention, and control methods, is displayed clearly.

3) Interactive Hospital Locator:

- The hospital locator feature, powered by Leaflet.js, displays nearby falcon hospitals or clinics on an interactive map. The map loads quickly, and users can easily search for hospitals by location or proximity.

4) Chatbot Functionality:

- The chatbot integrated with Google Gemini provides instant answers to user queries related to falcon diseases, symptoms, and treatments. It is responsive and able to handle a wide range of questions.

C. Comparison of Random Forest and Naïve Bayes

Through extensive evaluation, Random Forest was found to outperform Naïve Bayes in terms of both accuracy and ability to handle complex relationships in the data. The Random Forest model leverages an ensemble of decision trees, each trained on a random subset of data, which helps improve the model's robustness and generalization capability.

Why Random Forest was Chosen Over Naïve Bayes:

- Higher Accuracy: Random Forest consistently showed higher accuracy compared to Naïve Bayes, making it more reliable for disease prediction.
- Handling Non-Linearity: Random Forest is better suited for capturing complex, non-linear relationships between symptoms and diseases, which is critical in the context of falcon disease prediction.
- Reduced Overfitting: By averaging the predictions of multiple trees, Random Forest helps reduce overfitting, a common issue in simpler models like Naïve Bayes.

D. Future Work and Improvements

While the current implementation of the Falcon Doctor system demonstrates strong performance, there are several avenues for future enhancements:

1) Expanding the Dataset:

- The model can be further improved by expanding the dataset to include more diseases, symptoms, and different symptom combinations. This will help improve the model's generalization and predictive power.

2) Real-time Data Integration:

- Incorporating real-time data from veterinary clinics or hospitals can help improve disease prediction accuracy by ensuring the model stays updated with the latest health trends for falcons.

3) Personalized Recommendations:

- The system could be enhanced with personalized health tracking and alerts based on a falcon's health history, improving overall user engagement and disease prevention strategies.

4) User Feedback Integration:

- Continuously gathering and integrating user feedback could help improve the system by allowing it to adapt to new trends or emerging diseases.

VII. CONCLUSION

The Falcon Doctor project aims to revolutionize the way falcon breeders manage the health of their birds by leveraging artificial intelligence for disease detection and prediction. By integrating a trained Random Forest model, the system provides accurate disease predictions based on user-selected symptoms, helping falcon breeders and caretakers make informed decisions quickly. Unlike traditional veterinary methods that may require expert availability and manual diagnosis, Falcon Doctor offers a faster, more accessible solution through its interactive web-based interface. The prediction results are not only limited to identifying the most probable disease but also include vital information such as disease overview, transmission methods, preventive measures, control strategies, and health alerts, thereby offering a complete understanding of the condition. To further support users, the system incorporates a geolocation feature that enables easy identification of nearby falcon clinics and hospitals for timely medical intervention.

Additionally, the integration of a chatbot powered by Gemini allows for real time conversational support, enabling users to ask questions, clarify doubts, and receive instant responses related to falcon health and care. The user-friendly interface and features like feedback submission and password management make the system accessible to users with varying levels of technical knowledge. On the administrative side, the system provides functionalities to manage users, hospitals, and feedback, ensuring the platform remains organized and updated. By comparing machine learning models during development, the project demonstrated the effectiveness of Random Forest over Naïve Bayes using evaluation metrics such as accuracy, precision, recall, and F1-score. This model selection ensures reliable and consistent performance in disease prediction. The Random Forest model achieved 98.70% accuracy. Overall, Falcon Doctor is a significant step toward modernizing avian healthcare by combining technology, data, and expert insights into one platform.

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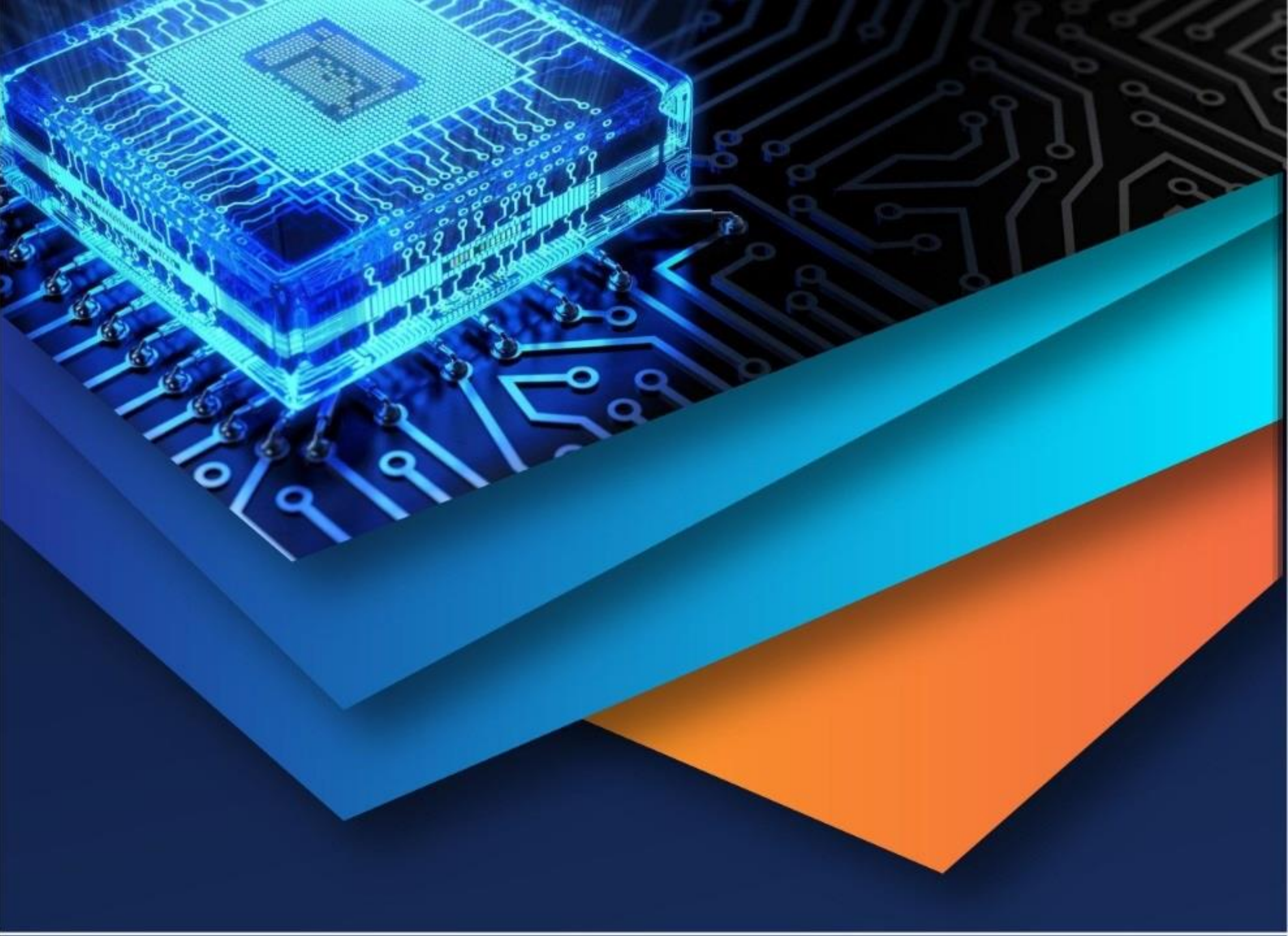

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