POULTRY HEALTH MONITORING THROUGH VOCALIZATION FOR DISEASE DETECTION

21CSC305P/MACHINE LEARNING PRACTICE
PROJECT REPORT

Submitted by

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Under the guidance of

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of

BACHELOR OF TECHNOLOGY

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COLLEGE OF ENGINEERING AND TECHNOLOGY

SRM
INSTITUTE OF SCIENCE & TECHNOLOGY
(Deemed to be University u/s 3 of UGC Act, 1956)
TIRUCHIRAPPALLI

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BONAFIDE CERTIFICATE

Certified that this project report titled **POULTRY HEALTH MONITORING THROUGH VOCALIZATION FOR DISEASE DETECTION** is the bonafide work of **MEGHAVARSHINI M (RA2211026050054)** and **MRISHIKA D (RA2211026050061)** who carried out the project work under my supervision. Certified further, that to the best of my knowledge the work reported herein does not form any other project report or dissertation on the basis of which a degree or award was conferred on an occasion on this or any other candidate.

SIGNATURE	SIGNATURE
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Submitted for the project viva-voce held on___________ at SRM Institute of Science and Technology, Trichy.

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DECLARATION

We hereby declare that the entire work contained in this project report titled **POULTRY HEALTH MONITORING THROUGH VOCALIZATION FOR DISEASE DETECTION** has been carried out **by MEGHAVARSHINI M (RA2211026050054)** and **MRISHIKA D (RA2211026050061)** at SRM Institute of Science and Technology, Trichy, under the guidance of Dr. P.K.A Chitra, Associate Professor, School of Computing.

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ABSTRACT

Detecting diseases in poultry early is essential to protect flock health, improve animal welfare, and avoid economic losses. Traditional methods of spotting illnesses often involve manual observation, which can be slow and labour-intensive, allowing diseases to spread before intervention. This project, titled "**Poultry Health Monitoring through Vocalization Analysis for Early Disease Detection**" introduces an automated system that analyses the sounds (vocalisations) made by poultry to identify potential health issues early, without needing direct physical inspection.The system works by recording poultry vocalisations and using machine learning to recognize patterns in the sounds. It collects a wide range of audio samples from healthy and unhealthy birds, creating a database of vocalisations that help identify differences in sound related to specific health conditions. Advanced techniques, like signal processing and deep learning, are applied to detect unusual sound patterns linked to stress, discomfort, or illness. This enables real-time monitoring, which means farmers can respond quickly when a potential issue is detected. Overall, this project aims to provide a practical tool for farmers to manage poultry health more effectively, reducing the spread of disease, improving animal welfare, and ultimately enhancing productivity in the poultry industry.

TABLE OF CONTENTS

1.1 INTRODUCTION

The poultry industry plays a critical role in global food production, supplying a significant portion of protein through meat and eggs. However, maintaining the health of poultry flocks is a constant challenge due to the risk of diseases that can spread quickly, impacting animal welfare, economic stability, and food safety. Early detection of health issues is essential for effective disease management, allowing farmers to isolate or treat affected birds before an illness can spread throughout the flock. Traditional methods for identifying poultry diseases involve manual inspections and observing symptoms, which can be time-consuming, labour-intensive, and prone to human error.

Recent advancements in machine learning and signal processing present new opportunities for non-invasive, automated monitoring systems that can improve health management in poultry farming. One promising approach involves analysing the vocalisations of birds, as changes in vocal patterns are often early indicators of stress or illness. Studies have shown that animals, including poultry, exhibit specific acoustic signals under different physiological and emotional states. These subtle vocal changes may precede visible symptoms, offering a valuable window for early detection and intervention.

This project, titled "**Poultry Health Monitoring through Vocalization Analysis for Early Disease Detection**" aims to develop a robust system that captures and analyses poultry vocalisations to detect early signs of disease. By creating a comprehensive dataset of poultry vocal sounds and applying machine learning algorithms to analyse these patterns, the project seeks to identify vocal characteristics associated with healthy and diseased states. The proposed system uses advanced audio signal processing techniques and deep learning models to monitor flock health continuously and autonomously.

The anticipated outcome is a reliable, real-time monitoring tool that assists farmers in maintaining flock health, reducing disease transmission, and minimising losses. This technology-driven solution could revolutionize health management in poultry farming, providing a cost-effective and scalable way to enhance animal welfare and operational efficiency in the industry.

1.2 PROBLEM STATEMENT:

The poultry industry struggles with early disease detection due to reliance on manual inspections, which are time-consuming and often identify diseases only after they have spread. This delay impacts animal welfare and leads to economic losses from decreased productivity and higher treatment costs. While changes in poultry vocalisations can signal early health issues, these subtle sounds are difficult for humans to detect, and current monitoring methods lack effective, non-invasive solutions.

This project aims to bridge this gap by developing an automated system that uses vocalisation analysis to detect early signs of disease in poultry. By analysing sound patterns, this tool will provide real-time alerts, allowing farmers to take early action to protect flock health, reduce losses, and enhance welfare in a scalable and efficient way.

1.3 OBJECTIVES:

This report aims to provide a comprehensive overview of the development and implementation of a POULTRY HEALTH MONITORING THROUGH VOCALIZATION FOR DISEASE DETECTION using both Python and Java, demonstrating the versatility and approachability of these programming languages. The main objectives are that it is an excellent platform for beginners to learn and practice programming fundamentals as it introduces concepts like user input, conditional statements, loops, and random number generation.

1.4 SCOPE AND MOTIVATION:

This project focuses on developing a vocalisation-based monitoring system for early disease detection in poultry. The scope includes:

1.Data Collection: Recording and analysing a wide variety of poultry vocalisations, capturing both healthy and diseased birds to build a comprehensive dataset.

2.Audio Feature Extraction and Deep Learning: Using the *Librosa* library for feature extraction, such as Mel-frequency cepstral coefficients (MFCCs) and spectral contrast, from the audio recordings. These features will then be input into deep learning models to identify patterns in the vocalisations that correlate with specific health conditions.

3.Real-Time Monitoring: Developing a system capable of continuously tracking vocalisation patterns in a poultry farm environment. This system will provide real-time alerts to farmers at the earliest indication of potential health issues.

4.Practical Application in Poultry Farms: Ensuring the system is designed for seamless integration into real-world poultry farms, emphasising ease of use, scalability, and minimal disruption to daily operations.

The system will primarily be aimed at improving disease management in poultry farms by providing farmers with an early warning system for potential health issues.

The motivation behind this project is to address the significant challenges poultry farmers face in detecting diseases early, which often results in high costs due to decreased productivity, increased mortality, and extensive treatment needs. Traditional methods of disease detection, such as manual inspection, are often slow and reactive, allowing diseases to spread before action can be taken. Vocalization analysis offers a non-invasive, continuous, and efficient solution to this problem. By leveraging technology to monitor vocal patterns, this project aims to provide a proactive and cost-effective method for improving poultry health management, reducing the economic impact of disease outbreaks, and enhancing overall animal welfare in the industry.

2.EXISTING MODELS

The poultry industry is one of the most significant sectors in global food production, providing essential protein sources through meat and eggs. However, poultry farming is constantly under threat from various diseases that can lead to severe economic losses, affect animal welfare, and even result in food safety concerns. Early disease detection in poultry is crucial for reducing the spread of diseases, ensuring healthy flocks, and maintaining optimal productivity.

Traditional methods of disease detection rely heavily on visual inspection, manual monitoring, and physical examinations, which are often time-consuming, labour-intensive, and reactive. These methods detect diseases only after the symptoms have become visible or after a significant amount of damage has been done. This delay in detection can result in the disease spreading throughout the flock, leading to higher mortality rates, decreased productivity, and increased treatment costs.

Recent advancements in artificial intelligence (AI), machine learning (ML), and signal processing have opened new possibilities for the non-invasive and early detection of poultry diseases. One such innovative approach involves using vocalisation analysis, where changes in poultry sounds can be indicators of disease or distress. Vocalisations in animals, including poultry, are linked to their physiological and emotional states.

This project aims to develop a system that analyses these vocalisations using machine learning and signal processing techniques to detect early signs of illness in poultry, providing a proactive solution to disease management in poultry farming.

2.1Existing Models in Poultry Health Monitoring:

While vocalisation analysis is a novel approach for early disease detection in poultry, there are several existing models and technologies that lay the foundation for this project. Below are some of the current methods used for poultry health monitoring:

1. Visual and Behavioral Health Monitoring Systems

The most widely used methods for detecting diseases in poultry are visual inspections and behavioural monitoring. These systems involve manually observing poultry for signs of illness such as changes in behaviour, posture, or physical appearance, including swelling, lethargy, or reduced activity levels. Visual health monitoring is often coupled with behavioural analysis, where changes in feeding behaviour, movement patterns, or social interactions are tracked.

Limitations:

- Visual methods often detect symptoms only after the disease has progressed, making early detection challenging.
- These systems are labour-intensive and require constant monitoring of large flocks, which can be impractical for large-scale operations.
- The subjective nature of human observation increases the potential for error and inconsistency in identifying health issues.

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2. Sensor-Based Health Monitoring Systems

With the rise of the Internet of Things (IoT) and wearable technology, sensor-based monitoring systems have gained popularity. These systems use a range of sensors, including temperature sensors, motion sensors, and RFID tags, to monitor the physical conditions and behaviour of poultry. For example, activity levels can be measured to detect reduced movement, or body temperature can be tracked to identify fever, a common symptom of infection.

Limitations:

- Sensor-based systems often require extensive installation and maintenance, adding costs to the operation.

- These systems can monitor only physical parameters and are unable to detect subtler, early-stage symptoms of disease, such as those that affect vocalisations before physical symptoms emerge.
- Wearable sensors can sometimes be uncomfortable for the poultry, which may impact their behaviour or well-being.

3. Sound-Based Monitoring Systems for Stress Detection

In recent years, researchers have started exploring the potential of sound analysis in animal health monitoring, particularly in detecting stress. Poultry, like other animals, change their vocalisations when under stress or in pain. For example, a chicken may produce higher-pitched or more frequent calls when experiencing stress due to environmental factors or injury.

Various studies have been conducted to analyse poultry vocalisations to detect stress, fear, or discomfort caused by changes in temperature, overcrowding, or human intervention. These studies typically use machine learning techniques to classify vocalisations and determine whether the bird is under distress.

Limitations:

- Sound-based systems primarily focus on detecting stress rather than disease, and the relationship between vocalisation changes and specific diseases is still not well understood.

- Stress and illness may produce similar vocalisation patterns, making it difficult to distinguish between them.
- Data collection for training these models is time-consuming and requires large, annotated datasets, which are not always available.

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4. Image and Video-Based Health Monitoring

Some advanced systems use image processing and computer vision techniques to detect health issues in poultry. Thermal cameras, for example, can detect changes in body temperature that may indicate infection or disease. Similarly, high-resolution cameras can capture visual anomalies such as swelling or skin lesions caused by disease.

Limitations:·

- Image-based systems often require sophisticated and expensive hardware, such as high-definition cameras or thermal sensors, which may not be affordable for all poultry farms.
- Like visual inspections, these systems typically detect diseases only after they have progressed to a visible stage, reducing their effectiveness for early disease detection.

5. Machine Learning for Disease Classification

Machine learning models, such as support vector machines (SVM), decision trees, and deep learning networks, have been applied to classify diseases based on visual and sensor data. These models can analyse patterns in the data and classify whether poultry are healthy or infected. However, the majority of these models are trained on physical symptoms rather than on the subtle vocal changes that may indicate early-stage diseases.

Limitations:

- These models require large datasets of labelled data, which can be difficult to obtain for poultry diseases, especially when early symptoms are not visible.
- As with other methods, these models generally focus on classifying diseases once symptoms have appeared, rather than on providing early warnings.

2.2Gap in Existing Models:

While various systems exist for poultry health monitoring, none have fully explored the use of vocalisation analysis for **early disease detection** in poultry. The existing models focus on either detecting stress, behavioural changes, or visible symptoms of disease, but they do not capture the subtle, early-stage indicators of illness that may be reflected in vocalisation changes. There is a significant opportunity to bridge this gap by using machine learning to detect changes in poultry vocalisations that indicate early signs of disease before visible symptoms appear.

3.Proposed Solution: Poultry Health Monitoring through Vocalization Analysis

This project aims to address the gap in existing poultry health monitoring systems by developing an automated, non-invasive solution based on vocalisation analysis for early disease detection. The system will analyse the sounds made by poultry and use machine learning algorithms to detect anomalies that could indicate disease or discomfort. Below is an outline of the key components of the proposed solution:

1. Data Collection

The initial phase involves gathering a diverse dataset of poultry vocalizations. This dataset will capture sounds from both healthy and diseased birds under various conditions, accounting for differences in health states, stress levels, and environmental factors. These diverse audio samples will form a robust foundation for training deep learning models to recognize health-related vocal patterns in poultry.

2. Audio Feature Extraction

Once the vocalization data is collected, advanced signal processing techniques will be applied to extract key audio features using the *Librosa* library. Features such as frequency, pitch, tone, rhythm, and intensity will be analyzed to identify subtle differences in vocalization patterns. These features will enable the system to detect changes that may indicate illness or distress in poultry.

3. Deep Learning Classification

The extracted audio features will be used to train deep learning models to classify the vocalizations based on poultry health status. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) will be explored to detect and learn patterns that distinguish healthy vocalizations from those associated with early disease symptoms.

4. Real-Time Monitoring and Alert System

The final system will continuously monitor poultry vocalizations in real-time, analyzing the sounds to detect anomalies that could signify early signs of disease. When abnormal vocal patterns are detected, the system will alert the farmer immediately, enabling early intervention and effective disease management.

5. Deployment in Poultry Farms

The system will be designed for easy deployment and scalability across poultry farms of varying sizes, from small family-run operations to large industrial farms. By utilizing low-cost microphones and affordable computing devices, such as Raspberry Pi, this solution aims to make advanced health monitoring accessible and feasible for poultry farmers at any scale.

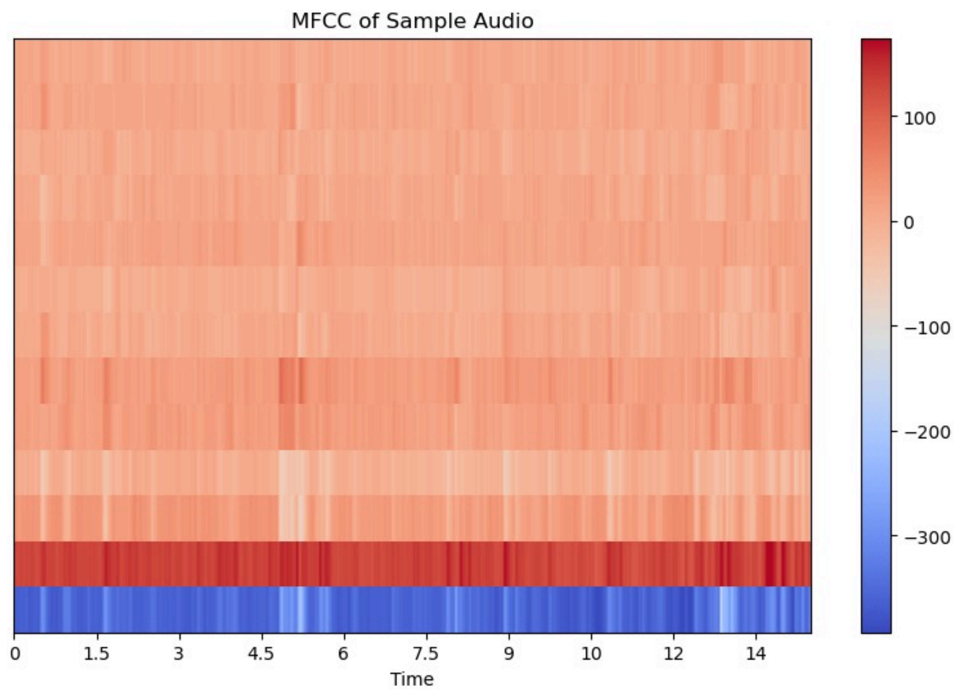
4.DATA PREPROCESSING

```python
import os
import librosa
import pandas as pd
import numpy as np

DATASET_PATH = r"C:\Users\Megha Mohan\ML Project\Chicken_Audio_Dataset"
CSV_PATH = "ffff.csv"
SAMPLE_RATE = 22050
NUM_MFCC = 13
N_FFT = 2048
HOP_LENGTH = 512


def save_mfcc(dataset_path, csv_path, num_mfcc=NUM_MFCC, n_fft=N_FFT, hop_length=HOP_LENGTH):

    data = {
        "filename": [],
        "label": []
    }

    for i in range(1, num_mfcc + 1):
        data[f"mfcc_{i}"] = []

    for i, (dirpath, dirnames, filenames) in enumerate(os.walk(dataset_path)):

        if dirpath != dataset_path:
            semantic_label = os.path.basename(dirpath)
```

```python
            print(f"\nProcessing genre folder: {semantic_label}")

            for f in sorted(filenames):
                file_path = os.path.join(dirpath, f)
                print(f"Loading file: {file_path}")

                try:
                    signal, sample_rate = librosa.load(file_path, sr=SAMPLE_RATE)

                    mfcc = librosa.feature.mfcc(y=signal, sr=sample_rate,
                                                n_mfcc=num_mfcc, n_fft=n_fft, hop_length=hop_length)
                    mfcc = mfcc.T
                    mfcc_mean = np.mean(mfcc, axis=0)
                    data["filename"].append(file_path)
                    data["label"].append(i - 1)


                    for j in range(num_mfcc):
                        data[f"mfcc_{j+1}"].append(mfcc_mean[j])

                except Exception as e:
                    print(f"Could not process file {file_path}. Error: {e}")

    df = pd.DataFrame(data)

    try:
        df.to_csv(csv_path, index=False)
        print(f"MFCCs successfully saved to {csv_path}")
```

MFCC

```
import librosa.display
file_path = df['filename'][0]
signal, sr = librosa.load(file_path, sr=22050)
mfcc = librosa.feature.mfcc(y=signal, sr=sr, n_mfcc=NUM_MFCC, n_fft=2048, hop_length=512)

plt.figure(figsize=(10, 6))
librosa.display.specshow(mfcc, x_axis='time', sr=sr)
plt.colorbar()
plt.title('MFCC of Sample Audio')
plt.show()
```



CSV file Obtained

filename	label	mfcc_1	mfcc_2	mfcc_3	mfcc_4	mfcc_5	mfcc_6	mfcc_7	mfcc_8	mfcc_9	mfcc_10	mfcc_11	mfcc_12	mfcc_13
C:\Users\	0	-348.325	133.6691	20.97174	-7.3456	22.31075	27.61396	5.742672	0.750243	13.71536	7.434586	3.566802	9.746097	7.396066
C:\Users\	0	-420.268	125.8755	48.85971	-3.77958	16.96293	31.87621	-6.92958	10.26215	16.47821	6.0126	8.807028	5.673353	5.60355
C:\Users\	0	-321.062	96.58236	31.92276	32.67665	9.740272	37.76519	0.046272	9.525447	15.95474	12.80832	-5.46047	15.56184	1.49953
C:\Users\	0	-317.604	100.7468	38.83309	35.75227	6.232172	42.8549	-1.07573	9.490542	15.95652	13.02963	-3.1711	16.47484	3.683671
C:\Users\	0	-302.06	106.3987	28.51061	31.94538	9.838884	42.95917	-2.85654	13.16655	17.85768	9.811583	-3.67703	13.69833	1.422633
C:\Users\	0	-307.625	109.4476	31.67873	22.80333	-2.32683	37.09967	-0.56945	5.980812	13.51993	16.00085	-4.33	16.52232	2.05195
C:\Users\	0	-335.517	93.59374	42.30287	35.75702	1.42434	34.54232	3.866659	8.212596	10.66096	15.50548	-4.58275	17.01623	0.266166
C:\Users\	0	-333.368	90.19494	39.999	38.67285	2.95187	35.96098	2.220271	9.666431	12.11753	12.93827	-4.69689	15.26643	0.410065
C:\Users\	0	-331.345	85.77242	35.91235	34.79213	1.31988	41.52587	0.554654	11.56018	12.90267	13.32068	-2.89736	14.92309	3.133822
C:\Users\	0	-338.133	83.9268	38.74938	35.92865	2.257529	40.66169	3.07751	9.840149	9.945959	15.41122	-5.09391	14.36901	2.128336
C:\Users\	0	-248.836	116.2875	31.68458	10.71208	22.65069	26.4526	-22.4363	24.4249	0.688178	10.5446	-1.53765	7.903819	8.282299
C:\Users\	0	-241.804	110.7566	33.72463	20.18279	16.94651	27.90436	-14.3872	19.14601	2.914434	8.96188	-3.43168	11.44977	8.264205
C:\Users\	0	-422	132.2669	42.59171	-11.4426	23.3727	21.68387	-3.51485	10.13672	8.289258	13.57535	-0.77155	10.10606	2.232262
C:\Users\	0	-238.318	115.8026	29.7011	16.34921	18.4532	26.33398	-13.56	18.81445	2.475543	11.1453	-6.65412	10.25515	6.868196
C:\Users\	0	-245.777	111.6776	38.99983	22.68744	18.74989	27.66183	-10.3074	21.16504	2.000095	10.98186	-2.84613	10.38368	5.434934
C:\Users\	0	-261.969	100.0393	34.80169	20.44548	19.35458	31.19774	-12.7537	21.4374	4.368619	14.60824	-11.9838	12.10896	7.523292
C:\Users\	0	-261.733	114.4602	50.13255	14.85645	8.530748	34.58476	-8.9283	17.9347	1.857655	17.3749	-9.03246	10.47242	6.338358
C:\Users\	0	-262.15	112.6332	44.36465	17.29433	8.14702	32.54236	-9.85697	16.87072	2.094369	13.89221	-7.12581	9.432282	6.981588
C:\Users\	0	-262.661	125.2771	36.19101	19.67988	10.96827	22.74235	-2.07633	7.264872	12.72654	6.764009	-3.48354	10.22221	2.498042
C:\Users\	0	-279.975	110.3878	36.56624	23.0418	9.71024	23.31965	-4.16408	6.786856	12.95529	5.708275	-6.61682	9.82068	3.066568
C:\Users\	0	-290.45	111.841	36.9825	23.5807	10.19844	19.95504	-0.53829	5.10616	11.6403	7.931619	-9.9828	9.627185	3.470548
C:\Users\	0	-286.659	111.8454	35.03069	22.45051	10.30977	19.42511	-2.61462	4.702968	12.99315	7.62398	-7.22722	10.83265	4.682386

MODEL CODE

```
import pandas as pd
import numpy as np
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv1D,Conv2D,MaxPooling1D, MaxPooling2D, Flatten, Dense, Dropout
from sklearn.model_selection import train_test_split
from tensorflow.keras.utils import to_categorical
```

```
CSV_PATH = "ffff.csv"
df = pd.read_csv(CSV_PATH)
```

```
X = df.drop(columns=['filename', 'label']).values
y = df['label'].values
```

```
NUM_MFCC = 13
X = X.reshape(len(X), NUM_MFCC, 1)
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
num_classes = len(np.unique(y))
y_train = to_categorical(y_train, num_classes)
y_test = to_categorical(y_test, num_classes)
```

```
model = Sequential()
model.add(Conv1D(32, 3, activation='relu', input_shape=(NUM_MFCC, 1)))
model.add(MaxPooling1D(2))
model.add(Flatten())
model.add(Dense(128, activation='relu'))
model.add(Dense(num_classes, activation='softmax'))
```

```
from tensorflow.keras.callbacks import EarlyStopping

early_stopping = EarlyStopping(monitor='val_loss', patience=3, restore_best_weights=True)
```

```
model.fit(X_train, y_train, epochs=7, validation_data=(X_test, y_test), batch_size=32,callbacks=[early_stopping])
```

```
Epoch 1/7
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - accuracy: 0.8819 - loss: 0.3745 - val_accuracy: 0.8714 - val_loss: 0.3207
Epoch 2/7
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step - accuracy: 0.8806 - loss: 0.3498 - val_accuracy: 0.8857 - val_loss: 0.3218
Epoch 3/7
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step - accuracy: 0.8321 - loss: 0.4416 - val_accuracy: 0.8857 - val_loss: 0.2657
Epoch 4/7
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step - accuracy: 0.8455 - loss: 0.3585 - val_accuracy: 0.8571 - val_loss: 0.3370
Epoch 5/7
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step - accuracy: 0.8505 - loss: 0.3830 - val_accuracy: 0.9000 - val_loss: 0.2751
Epoch 6/7
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step - accuracy: 0.8959 - loss: 0.3174 - val_accuracy: 0.8857 - val_loss: 0.2422
Epoch 7/7
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - accuracy: 0.8841 - loss: 0.3265 - val_accuracy: 0.9143 - val_loss: 0.2389

<keras.src.callbacks.history.History at 0x23f94f20eb0>
```

```
loss, accuracy = model.evaluate(X_test, y_test)
print(f"Test Accuracy: {accuracy}")
```

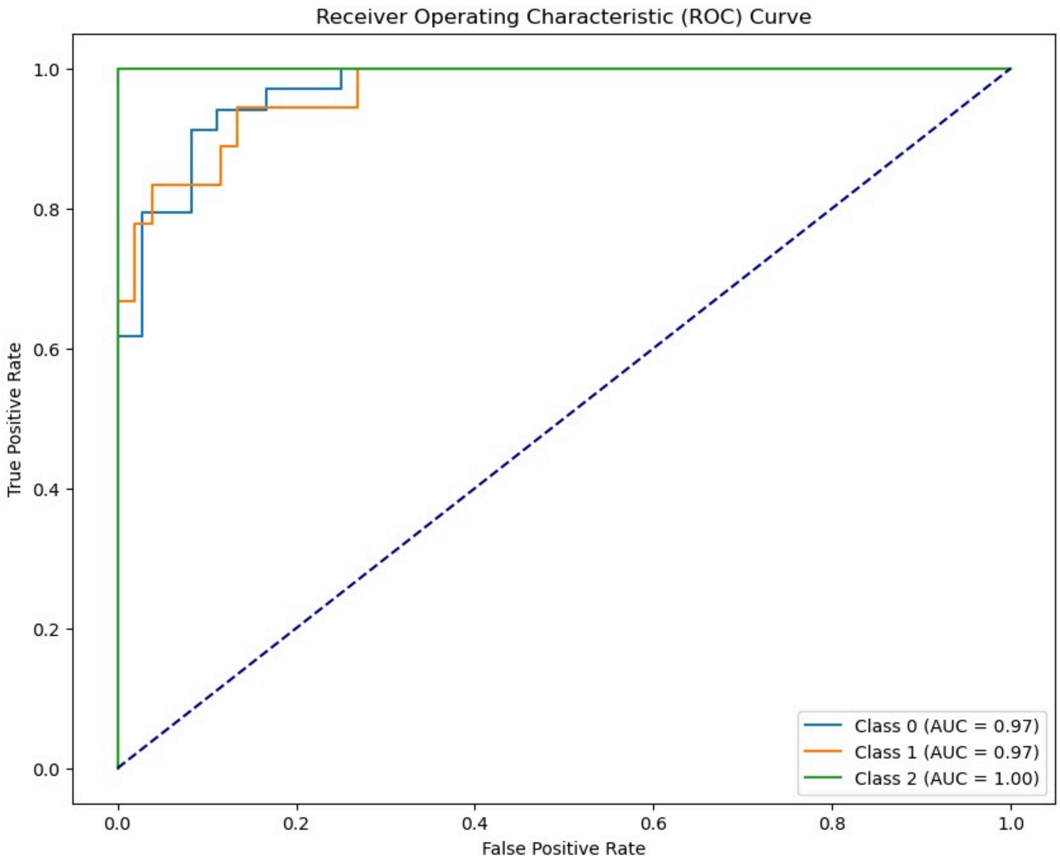
```
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.9259 - loss: 0.2485
Test Accuracy: 0.9142857193946838
```

```
model.save("mymodel1.keras")
```

ROC CURVE CODE

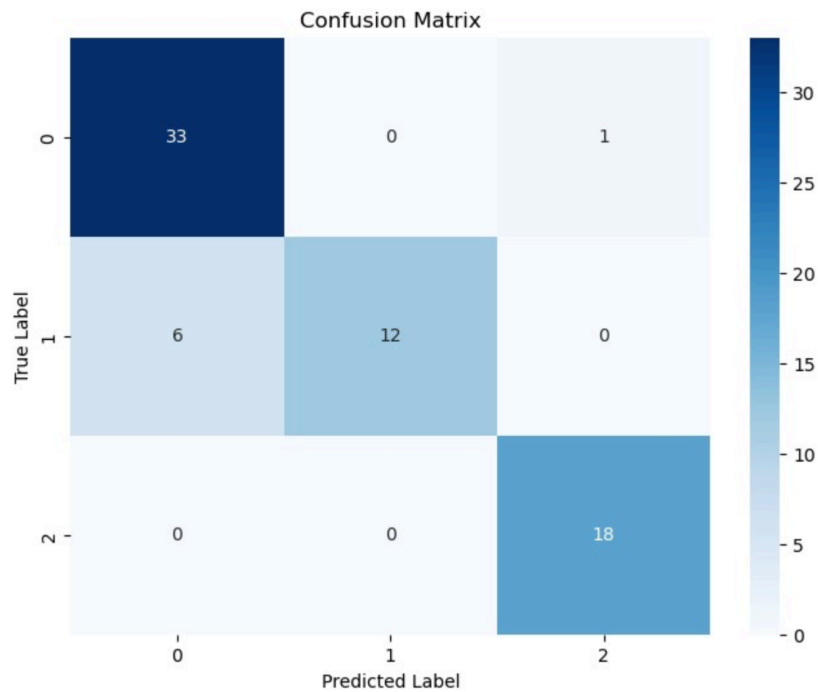
```
from sklearn.metrics import roc_curve, auc
from sklearn.preprocessing import label_binarize

y_test_bin = label_binarize(y_test, classes=np.unique(y))
y_pred_bin = new_model.predict(X_test)

plt.figure(figsize=(10, 8))
for i in range(num_classes):
    fpr, tpr, _ = roc_curve(y_test_bin[:, i], y_pred_bin[:, i])
    roc_auc = auc(fpr, tpr)
    plt.plot(fpr, tpr, label=f'Class {i} (AUC = {roc_auc:.2f})')

plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend(loc='lower right')
plt.show()
```

ROC CURVE GRAPH



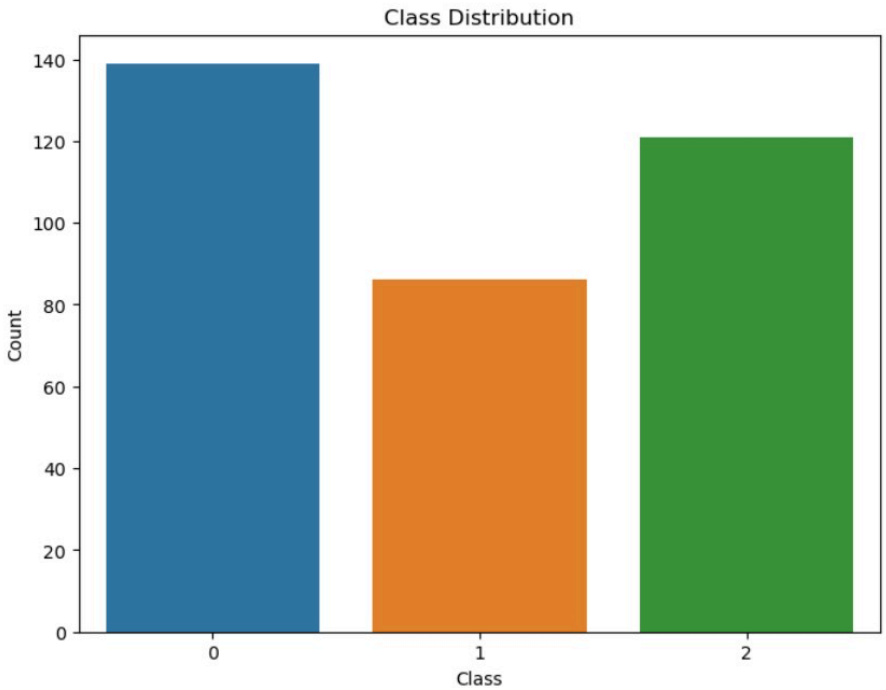
```python
from sklearn.metrics import confusion_matrix
import seaborn as sns

y_pred = np.argmax(new_model.predict(X_test), axis=1)

cm = confusion_matrix(np.argmax(y_test, axis=1), y_pred)

plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=np.unique(y), yticklabels=np.unique(y))
plt.title('Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```

```
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
```



CLASS DISTRIBUTION

```
plt.figure(figsize=(8, 6))
sns.countplot(x='label', data=df)
plt.title('Class Distribution')
plt.xlabel('Class')
plt.ylabel('Count')
plt.show()
```

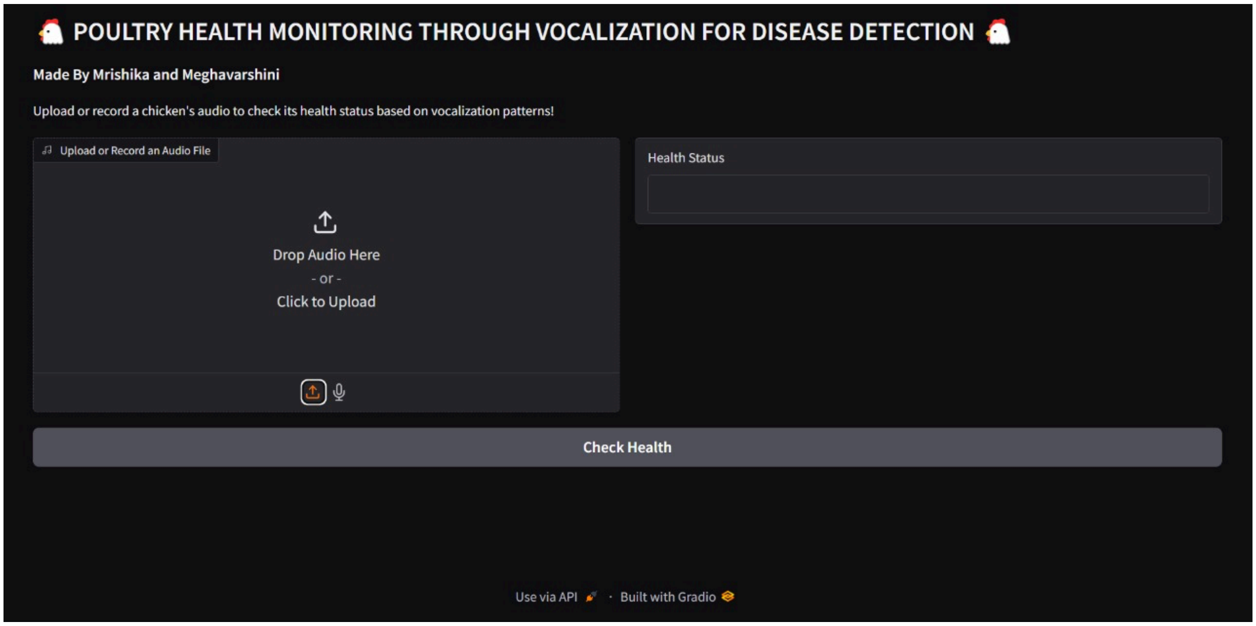


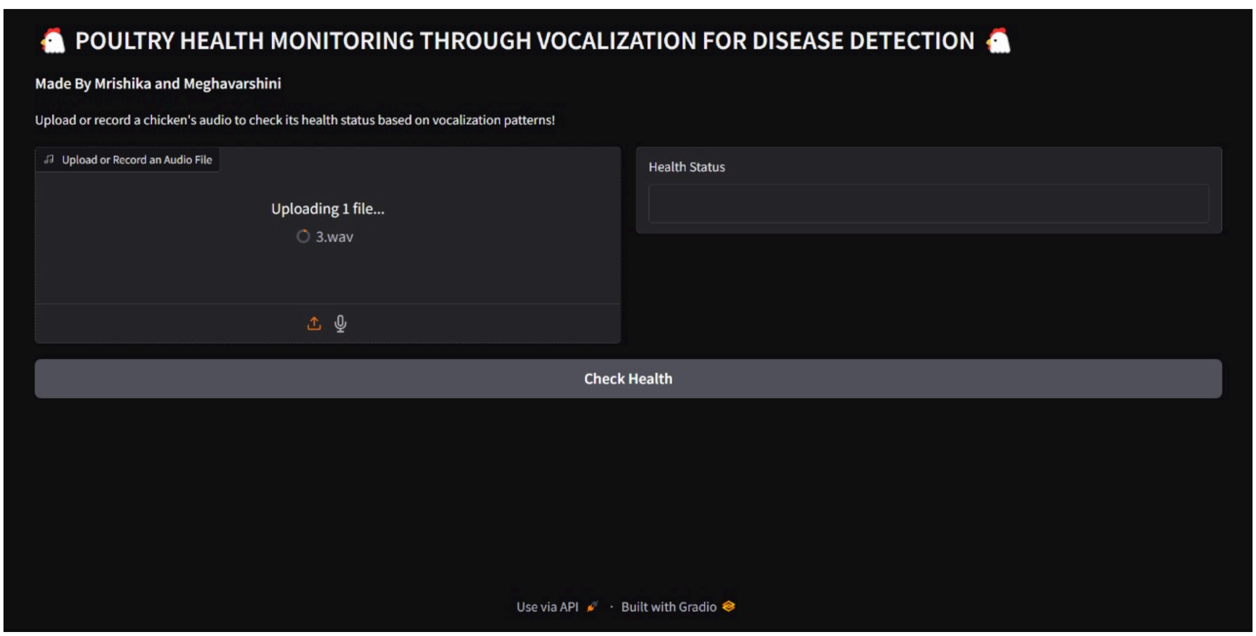
UI CODE

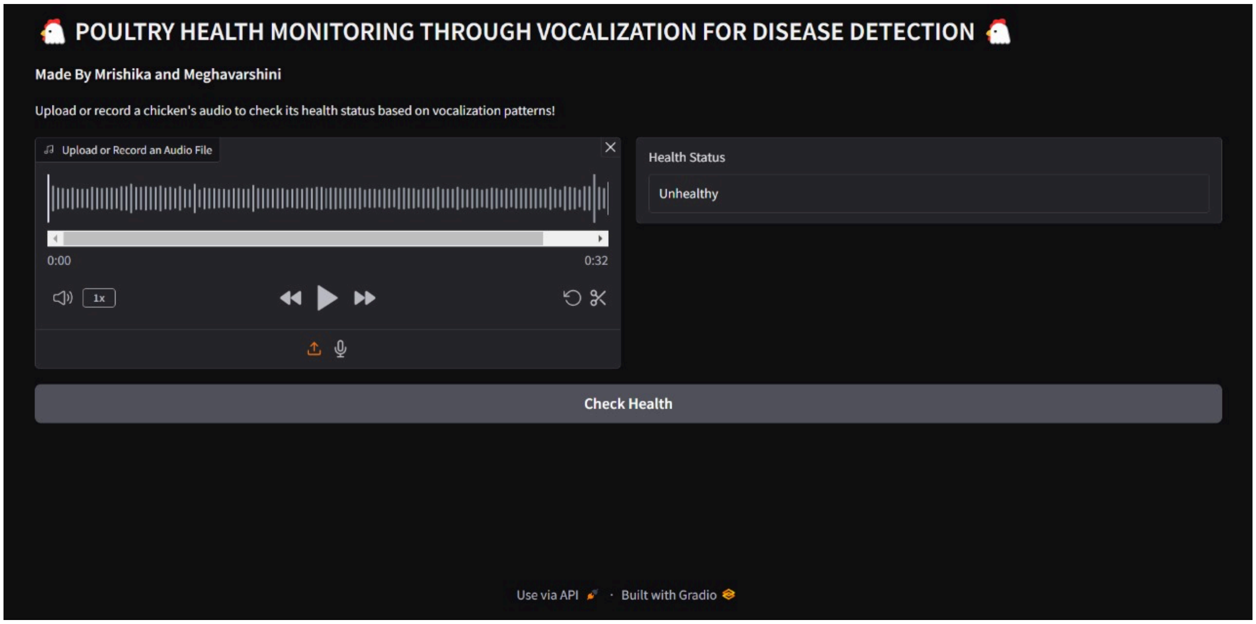
```
import gradio as gr
import numpy as np
import tensorflow as tf
import librosa

model = tf.keras.models.load_model("mymodel1.keras")

SAMPLE_RATE = 22050
NUM_MFCC = 13
N_FFT = 2048
HOP_LENGTH = 512

def predict_chicken_health(audio):
    signal, sample_rate = librosa.load(audio, sr=SAMPLE_RATE)
    mfcc = librosa.feature.mfcc(y=signal, sr=sample_rate, n_mfcc=NUM_MFCC, n_fft=N_FFT, hop_length=HOP_LENGTH)
    mfcc_mean = np.mean(mfcc.T, axis=0)

    mfcc_features = mfcc_mean.reshape(1, NUM_MFCC, 1)

    prediction = model.predict(mfcc_features)
    label = np.argmax(prediction, axis=1)

    health_status = "Healthy" if label == 0 else "Unhealthy"
    return health_status
```

```
title = " 🐔 POULTRY HEALTH MONITORING THROUGH VOCALIZATION FOR DISEASE DETECTION 🐔"
description = """
### Made By  Mrishika and Meghavarshini
Upload or record a chicken's audio to check its health status based on vocalization patterns!
"""

with gr.Blocks() as iface:
    gr.Markdown(f"# {title}")
    gr.Markdown(description)
    with gr.Row():
        audio_input = gr.Audio(type="filepath", label="Upload or Record an Audio File")
        output_text = gr.Textbox(label="Health Status")
    submit_button = gr.Button("Check Health")
    submit_button.click(predict_chicken_health, inputs=audio_input, outputs=output_text)

iface.launch()
```

GRADIO WEB APP






POULTRY HEALTH MONITORING THROUGH VOCALIZATION FOR DISEASE DETECTION
Made By Mrishika and Meghavarshini
Upload or record a chicken's audio to check its health status based on vocalization patterns!
Upload or Record an Audio File
0:00
0:32
1x
Health Status
Unhealthy
Check Health
Use via API
Built with Gradio

CONCLUSION

In conclusion, developing an automated, vocalization-based monitoring system for early disease detection in poultry represents a major advancement in health management within the poultry industry. Traditional approaches to disease monitoring, such as visual inspections, behavior-based assessments, and occasional sampling, while helpful, often detect issues only after the disease has spread within the flock. This lag results in increased mortality rates, higher veterinary costs, and decreased productivity, creating significant financial and operational challenges for poultry farmers. As the industry seeks to move toward more sustainable, efficient, and proactive farming practices, technology-driven solutions, such as this vocalization-based system, hold great promise for addressing these long-standing issues.

The significance of this project lies in its unique focus on vocalization analysis to detect early disease signs in poultry, an approach that is both non-invasive and continuous. Research shows that changes in vocalization are often one of the first signs of stress or illness in animals, including poultry. However, these changes can be subtle and undetectable by human hearing, especially on large farms with high bird densities where continuous manual monitoring would be impossible. By implementing machine learning algorithms capable of detecting these subtle vocal changes, this system offers farmers a new and effective way to identify potential health issues before they are visible through physical symptoms.

The system is designed to analyze subtle variations in the frequency, pitch, tone, rhythm, and intensity of poultry vocalizations. These audio features are known indicators of health and well-being in birds, with different conditions—such as respiratory diseases, infections, or nutritional deficiencies—causing distinct changes in vocal patterns. Through data collection and advanced signal processing, the system will build a comprehensive dataset of vocalizations that reflect various health states, from healthy to disease-affected. This data will then be processed using feature extraction techniques, leveraging tools such as the Librosa library to identify critical sound features and patterns associated with each health condition.

Using these extracted features, the system will train deep learning models to differentiate between healthy vocalizations and those that indicate early-stage diseases. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) will be employed to detect complex patterns within the data. CNNs are particularly effective for handling audio spectrograms and identifying spatial patterns, while RNNs excel in capturing temporal dependencies, which are crucial in analyzing the progression of vocal changes over time. By combining these models, the system can achieve high accuracy in classifying vocalizations, making it a reliable tool for real-time health monitoring in poultry.

The real-time monitoring capability of this system is a key feature, providing continuous tracking and analysis of vocal patterns within the farm environment. Equipped with low-cost, durable microphones and small-scale computing devices, such as the Raspberry Pi, the system can be easily installed in various types of poultry farms. These devices continuously record audio data, which is then analyzed by the machine learning model. When abnormal vocal patterns are detected, the system sends an immediate alert to the farmer, specifying the potential issue and suggesting early intervention steps. This real-time alerting system allows for prompt action, which can prevent the disease from spreading across the flock and minimize the severity of health impacts on affected birds.

The proactive nature of this system significantly reduces the need for extensive treatment and broad-spectrum antibiotics, aligning with the industry's shift towards antibiotic-free and sustainable farming. Early disease detection enables farmers to focus on isolated cases before they escalate, making treatment more targeted and reducing the risk of antibiotic resistance. In addition to enhancing the health of individual flocks, this approach supports public health objectives by limiting the overuse of antibiotics in the food production process. This benefit positions the vocalization-based monitoring system as a valuable asset in the movement toward safer, healthier, and more sustainable food production systems.

Another substantial advantage of this system is its scalability and affordability, which make it accessible to farms of all sizes, from small family-run poultry operations to large-scale industrial complexes. Small-scale farmers, who may lack the resources for complex health monitoring systems, stand to benefit significantly from a low-cost, effective disease monitoring solution. Large farms, on the other hand, face the challenge of monitoring thousands of birds spread over expansive areas, a task that would be both impractical and prohibitively expensive to perform manually. The use of inexpensive microphones and compact computing hardware allows for cost-effective deployment across large areas, creating a flexible solution that is adaptable to diverse operational needs. This flexibility not only encourages widespread adoption but also increases the overall resilience and productivity of the poultry farming industry.

Beyond poultry health monitoring, this system also holds broader implications for animal welfare and agricultural technology. By providing a continuous, non-invasive means of assessing animal health, vocalization-based analysis represents an advancement in welfare-centered practices. Traditional health assessments, such as manual handling or invasive sampling, can be stressful for animals and labor-intensive for farm workers. This system, by contrast, requires no physical contact, thereby reducing stress for the animals and simplifying daily operations for farmers. The principles underlying this project could inspire similar monitoring systems for other livestock, extending the impact of this technology to various agricultural sectors.

The benefits of early disease detection extend beyond economic gains to encompass a broader commitment to sustainable farming. As consumers become increasingly aware of animal welfare and environmental sustainability, the demand for ethically produced, antibiotic-free poultry products is growing. By adopting this innovative monitoring system, poultry farms can demonstrate a commitment to responsible farming practices, which may enhance their reputation and competitiveness in the market. Consumers, in turn, benefit from improved food safety and quality, knowing that their products come from farms that prioritize animal health and welfare.

From a technological perspective, this project highlights the potential for deep learning applications in real-world agricultural settings. The integration of AI-driven tools with practical farm applications showcases the feasibility of implementing complex machine learning models outside of traditional laboratory environments. In creating a robust, data-driven approach to poultry health monitoring, this project reflects the value of interdisciplinary collaboration, merging insights from animal science, signal processing, and machine learning. The success of this system could serve as a model for future AI-powered solutions in agriculture, paving the way for smart farming practices that are both efficient and compassionate.

Overall, this vocalization-based monitoring system stands to revolutionize poultry health management by offering a comprehensive, proactive, and cost-effective approach to disease detection. With real-time alerts, scalable deployment, and the capacity to reduce reliance on antibiotics, this system addresses several pressing challenges within the poultry industry. Farmers benefit from a tool that enhances productivity and reduces the risk of disease outbreaks, while consumers gain greater assurance of ethical and sustainable food production practices. In the long term, this project has the potential to drive broader advancements in animal welfare, agricultural sustainability, and food security, contributing to a more resilient and innovative poultry industry.

In summary, the proposed system exemplifies the intersection of technology and agriculture, where intelligent systems meet real-world farming needs. By leveraging machine learning to analyze subtle vocal changes in poultry, this project offers a new perspective on health management, one that is preventative rather than reactive. The scalability and affordability of this solution ensure that it can be widely adopted, making it an accessible and powerful tool for poultry farmers worldwide. Through continuous monitoring and early intervention, this system has the power to transform poultry health practices, support ethical farming, and promote a more sustainable and secure agricultural future.

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