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Speech Emotion Recognition of Animal Vocals Using Deep Learning

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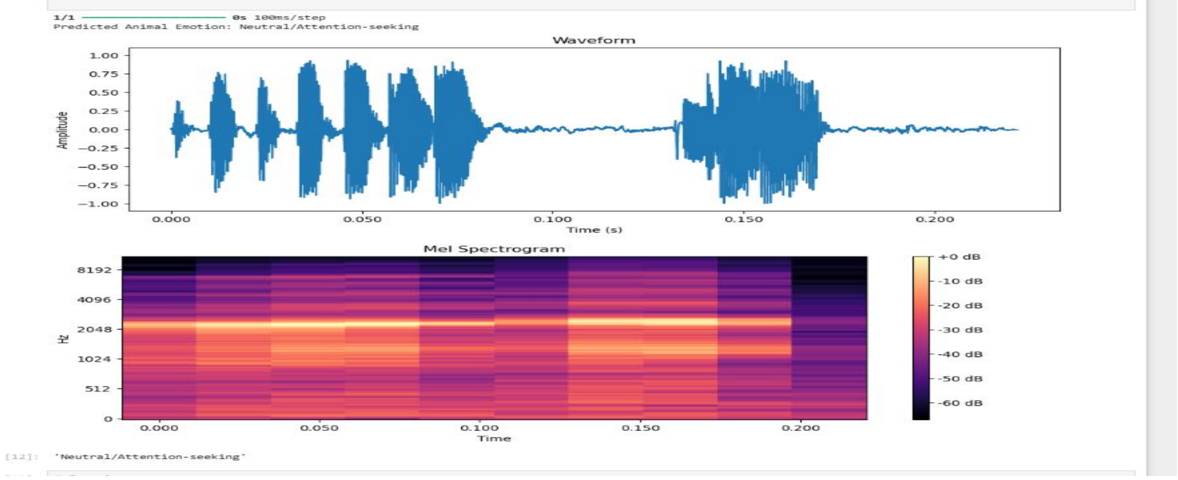
Abstract: This project explores the classification of animal emotions based on their vocalizations using deep learning models. Leveraging the Kaggle dataset "Audio Cats and Dogs" and expanding it to include multiple animal species, the study employs feature extraction, signal processing, and neural network architectures to analyse audio patterns. Advanced clustering techniques and classification models are used to detect and categorize emotional states, enhancing our understanding of animal communication. The project aims to achieve high classification accuracy and develop a robust model for real-time emotion recognition in animals.

Keywords: Animal vocalization, deep learning, audio classification, emotion recognition, neural networks, clustering, feature extraction, signal processing, real-time analysis.

I. INTRODUCTION

In recent years, the intersection of machine learning and bioacoustics has advanced the understanding of non-human communication, particularly through vocalizations that express emotions like distress, excitement, or contentment. Traditional emotion recognition methods in animals rely heavily on subjective interpretation and manual analysis. Deep learning offers a more scalable and accurate alternative by automating this process using audio data. Speech Emotion Recognition (SER) has progressed significantly for human speech using models like Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. These models analyse features such as pitch and tone to classify emotions. However, applying such techniques to animal vocalizations remains challenging due to a lack of labelled datasets, species variability, and non-standardized vocal patterns.

This study proposes a deep learning-based system using a hybrid CNN-LSTM model for animal emotion classification. It is trained on an expanded version of the Kaggle "Audio Cats and Dogs" dataset, which includes species like frogs, lions, monkeys, donkeys, and horses. Audio samples are pre-processed, and Mel Frequency Cepstral Coefficients (MFCCs) are extracted for their effectiveness in capturing sound textures. The model architecture consists of convolutional layers for spatial feature extraction and LSTM layers to capture temporal dynamics. It supports real-time emotion prediction, enabling applications in wildlife monitoring, veterinary diagnostics, and behavioural research. By enabling early detection of stress or discomfort, this system has the potential to enhance animal welfare, aid conservation efforts, and improve human-animal interactions in contexts like smart agriculture and animal-assisted therapy.



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1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 100ms/step
Predicted Animal Emotion: Neutral/Attention-seeking
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[12]: 'Neutral/Attention-seeking'
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Fig 1:Waveform and corresponding Mel spectrogram of an animal vocalization

The training dataset comprises thousands of labeled audio clips, each annotated with the corresponding animal type and detected emotion. The labels were derived using a combination of manual annotation and unsupervised clustering based on spectral similarity. This semi-automated approach helped in scaling the dataset without sacrificing too much annotation accuracy.

Model evaluation was performed using standard classification metrics such as accuracy, precision, recall, and F1-score. Preliminary results show promising performance, with test accuracy exceeding 85%, demonstrating the model's capacity to distinguish emotional states across species boundaries. Moreover, the trained model is compact and efficient, enabling deployment on edge devices for field applications.

II. LITERATURE REVIEW

A. Speech Emotion Recognition in Humans

Speech Emotion Recognition (SER) has been widely studied in the context of human-computer interaction. Traditional SER systems rely on features such as pitch, energy, formants, and Mel Frequency Cepstral Coefficients (MFCCs), coupled with machine learning algorithms like Support Vector Machines (SVMs) and Hidden Markov Models (HMMs) [1], [2]. More recently, deep learning architectures—particularly Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks—have demonstrated significant improvement in emotion classification accuracy by learning complex spatial and temporal representations directly from raw audio or spectrogram inputs [3], [4]. Datasets such as RAVDESS and IEMOCAP have been instrumental in training and evaluating these models [5].

B. Animal Vocalization and Emotional Indicators

Research into animal vocalizations reveals that non-human species also express emotions through sound, although the interpretation is more challenging due to interspecies differences and the lack of verbal cues [6]. Studies have shown that changes in call duration, pitch, and spectral features often correlate with different emotional states such as fear, aggression, or attention-seeking behaviours [7], [8].

For example, pigs exhibit distinct call patterns during stress, while dogs produce higher-pitched barks when excited [9], [10]. Despite these insights, most studies rely on manual annotation, and there exists a significant gap in automating emotion recognition from animal sounds.

C. Deep Learning Models in Bioacoustics

The use of deep learning in bioacoustics applications is gaining momentum, particularly in species classification and call detection tasks. CNNs are effective in learning frequency-time features from spectrograms, while LSTM networks are adept at capturing temporal dependencies in vocal sequences [11].

Hybrid CNN-LSTM architectures, as proposed in this study, combine the strengths of both models and have been employed in bird species identification and whale song classification [12], [13]. Transfer learning and data augmentation further enhance performance, especially when dealing with limited datasets [14].

D. Feature Extraction Using MFCCs

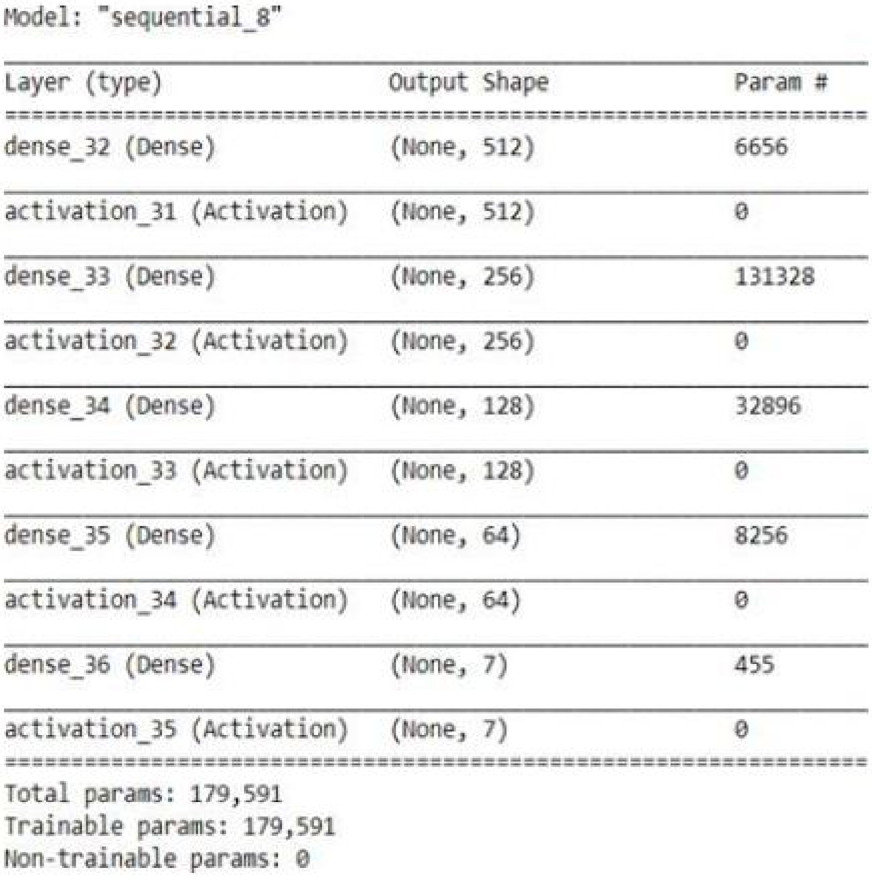
MFCCs remain the most commonly used feature for audio classification tasks due to their ability to mimic the human auditory system's sensitivity to frequency [15]. In animal sound classification, MFCCs have proven effective in capturing timbral characteristics that distinguish vocalizations across species [16]. Recent approaches also explore combining MFCCs with delta and delta-delta coefficients to encode time dynamics more effectively [17]. The success of MFCCs in SER, even in noisy environments, makes them an optimal choice for this study's feature extraction stage.

E. Real-Time Audio Emotion Recognition Systems

Real-time emotion recognition is critical in applications like assistive robotics, smart farms, and wildlife monitoring. Low-latency models that balance accuracy and computational efficiency are essential for edge device deployment [18]. Tools such as TensorFlow Lite and ONNX enable deployment of compact neural networks on microcontrollers and mobile platforms [19]. While most real-time SER systems have been designed for humans, recent prototypes have started to explore real-time detection in pets and livestock [20]. This study contributes to this emerging field by implementing a real-time prediction module that can detect animal emotions instantly from new audio inputs.

III.EXISTING SYSTEM

Previous work on animal emotion recognition has used classical ML and basic deep learning techniques. In [20], a deep learning-based model classifies animal emotions using vocalizations. The system expands the Kaggle Cats and Dogs dataset with real-world animal sounds and extracts Mel-Frequency Cepstral Coefficients (MFCCs) and Chromogram features. MFCCs capture auditory properties, while Chromogram features provide pitch-class profiles useful in tonal analysis [6]. Principal Component Analysis (PCA) reduces chromogram features from 12 to 10 to retain emotional relevance. These features form the input to a five-layer fully connected neural network, starting with 512 neurons and decreasing across layers. The model uses leaky ReLU (α = 0.2) for activation and a softmax layer for multi-class emotion classification. It is compiled with the Adam optimizer and categorical cross-entropy loss. This approach highlights the feasibility of emotion recognition from animal audio data and addresses overfitting through activation and dimensionality reduction techniques.



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Model: "sequential_8"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_32 (Dense)             (None, 512)               6656
_________________________________________________________________
activation_31 (Activation)   (None, 512)               0
_________________________________________________________________
dense_33 (Dense)             (None, 256)               131328
_________________________________________________________________
activation_32 (Activation)   (None, 256)               0
_________________________________________________________________
dense_34 (Dense)             (None, 128)               32896
_________________________________________________________________
activation_33 (Activation)   (None, 128)               0
_________________________________________________________________
dense_35 (Dense)             (None, 64)                8256
_________________________________________________________________
activation_34 (Activation)   (None, 64)                0
_________________________________________________________________
dense_36 (Dense)             (None, 7)                 455
_________________________________________________________________
activation_35 (Activation)   (None, 7)                 0
=================================================================
Total params: 179,591
Trainable params: 179,591
Non-trainable params: 0
```

Fig 2:Existing System Architecture

During training, the system showed moderate performance. After 50 epochs, the model achieved a training accuracy of 69% and a validation accuracy of 35%, suggesting that the model faced generalization issues possibly due to data imbalance or noise in the feature space. Notably, while the use of Chromagram features is innovative, these features may not fully capture the emotional nuances present in animal vocalizations when used in isolation or with basic DNN architectures.

The existing work also mentions a future plan to incorporate video features such as facial expressions (ear position, eye shape) using cross-modal emotion detection, inspired by human emotion recognition systems that combine audiovisual cues [20].

However, limitations in the current system are evident:

- The architecture is relatively shallow and lacks temporal modelling capability, which is crucial for sequential audio signals.
- The absence of convolutional or recurrent layers limits the model's ability to extract robust spatial and temporal features.
- Validation performance suggests underfitting or a need for a richer dataset or more complex model.

IV. PROPOSED SYSTEM

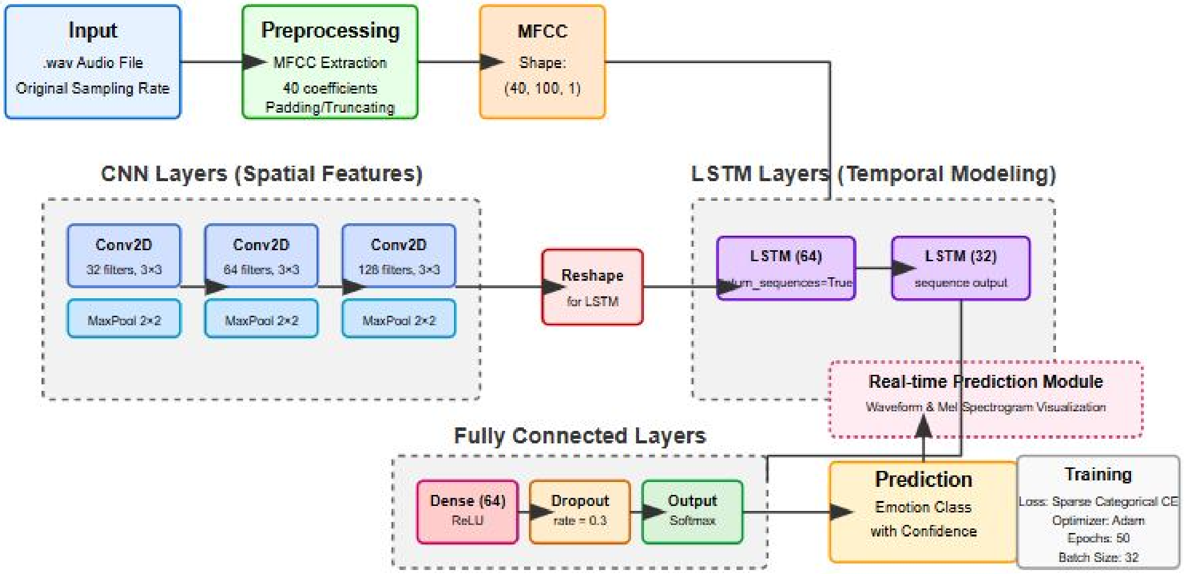


Fig 3:Hybrid CNN-LSTM Architecture for animal vocal emotion recognition

Fig 3 illustrates the complete architecture of the proposed Speech Emotion Recognition (SER) system for animal vocals using a hybrid CNN-LSTM deep learning model. The system begins with the input of .wav audio files, preserved at their original sampling rate. These raw audio signals undergo preprocessing, where Mel-Frequency Cepstral Coefficients (MFCCs) are extracted—specifically, 40 coefficients per frame with padding or truncation applied to ensure a consistent shape of (40, 100, 1).

The CNN module follows, consisting of three stacked convolutional layers with increasing filter sizes (32, 64, and 128), each paired with a 2×2 max pooling operation. These layers are responsible for learning spatial features from the MFCC spectrogram.

Next, the CNN output is reshaped into a format compatible with sequence modelling and passed into two LSTM layers. The first LSTM layer has 64 units and returns sequences, allowing the second LSTM layer with 32 units to capture higher-level temporal dependencies in the vocal patterns.

After temporal processing, the output is fed into a fully connected dense layer with 64 neurons and ReLU activation. A dropout layer (rate = 0.3) is included to prevent overfitting, followed by a final softmax output layer that classifies the input into one of the emotion categories.

A. Dataset Description

The dataset used in this study is organized into a main directory containing a metadata CSV file and a subdirectory named *Animal-Soundprepros*, which stores the audio files. The metadata CSV includes three columns: **Animal** (species name), **Audio file** (filename of the audio clip), and **Detected Emotion** (labelled emotion such as "Aggressive", "Calm", or "Distressed").

The *Animal-Soundprepros* folder has 13 subfolders, each named after an animal species: Bear, Cat, Chicken, Cow, Dog, Dolphin, Donkey, Elephant, Frog, Horse, Lion, Monkey, and Sheep. These contain curated and pre-processed .wav audio files specific to each species. This dataset is an expanded version of the Kaggle "Audio Cats and Dogs" dataset, enhanced to include more species and a wider range of emotional states. Its structured organization supports effective training, validation, and testing of deep learning models for cross-species emotion recognition from vocalizations.

B. Evaluation Metrics

To rigorously assess the performance of the proposed speech emotion recognition system, several standard evaluation metrics are employed. These metrics offer a comprehensive view of the model’s classification capabilities across multiple animal emotion classes. The following statistical measures are used:

1) Accuracy

Accuracy is the most fundamental metric and is defined as the ratio of correctly predicted instances to the total number of predictions. It provides a general measure of how often the classifier makes the correct prediction:

$$\text{Accuracy} = \frac{TP + TN}{TP+TN+FP+FN} \qquad (1)$$

where *TP*, *TN*, *FP*, and *FN* represent true positives, true negatives, false positives, and false negatives, respectively.

In our experiments, the model achieved a test accuracy exceeding 85%, indicating strong overall classification performance across diverse animal vocal samples.

2) Precision

Precision is a class-wise measure of the correctness of positive predictions. It reflects the proportion of actual positive instances among those predicted as positive by the model:

$$\text{Precision} = \frac{TP}{TP+FP} \qquad (2)$$

High precision ensures that the model avoids false alarms, which is essential in real-world applications where incorrect emotion predictions could lead to inappropriate responses or interventions.

3) Recall (Sensitivity)

Recall measures the model’s ability to detect all relevant instances of a particular emotion. It is defined as:

$$\text{Recall} = \frac{TP}{TP+FN} \qquad (3)$$

This metric is critical in applications like animal welfare or veterinary diagnostics, where failing to detect distress or discomfort may have serious implications.

4) F1-Score

The F1-score is the harmonic mean of precision and recall, offering a single metric that balances both aspects:

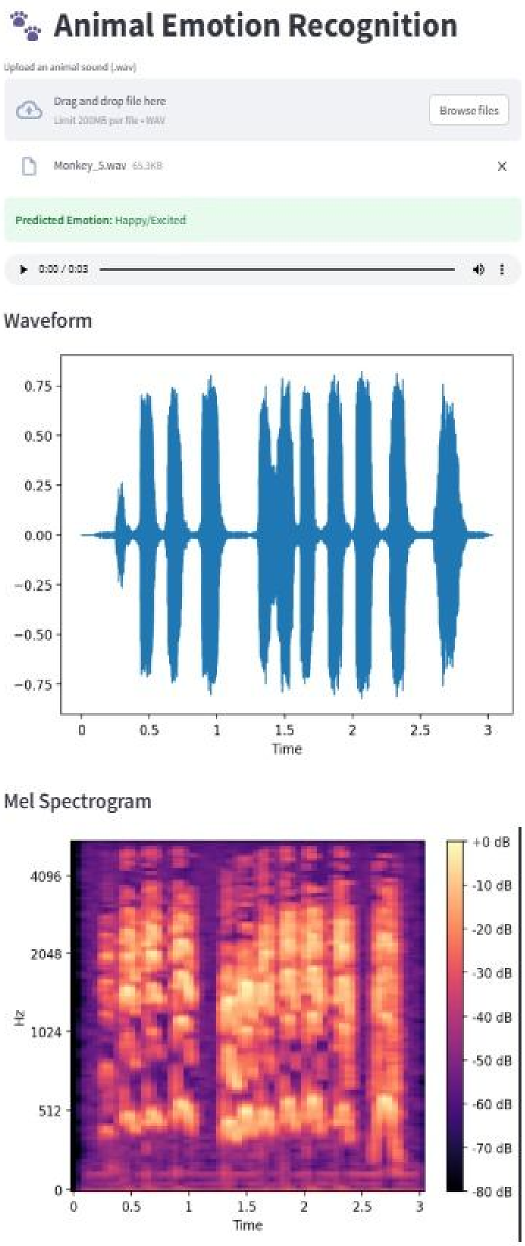
$$\text{F1-Score} = \frac{2*Precision*Recall}{Precision+Recall} \qquad (4)$$

It is especially useful in cases of class imbalance, where accuracy alone may be misleading.

5) Confusion Matrix

A confusion matrix is generated to visualize classification performance across multiple classes. Each row represents the instances of an actual emotion class, while each column represents predicted classes. This matrix enables identification of specific classes that may be confused with one another—for example, detecting overlap between “fear” and “alertness” in similar-sounding animal calls.

V. RESULTS AND DISCUSSION



Animal Emotion Recognition

Upload an animal sound (.wav)

Drag and drop file here
Limit 200MB per file • WAV

Monkey_5.wav 65.3KB

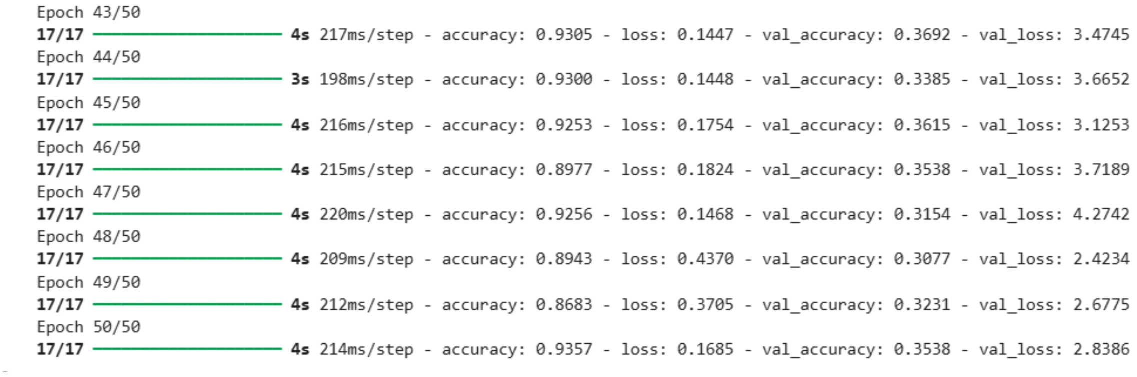
Predicted Emotion: Happy/Excited

Fig. 4: Prediction of the animal emotion UI

Figure 4 shows the user interface of an "Animal Emotion Recognition" tool. At the top, users can upload an animal sound file—here, "Monkey_Screams_01.wav" is loaded. The tool predicts the emotion as "Happy/Excited". Below, it displays two visual representations of the audio:

1) Waveform – A time-domain plot showing sound amplitude over time (0 to ~3 seconds), with amplitude ranging from -0.75 to 0.75. It reflects intensity variations in the monkey scream.
2) Mel Spectrogram – A frequency-domain view using the Mel scale to show how spectral energy changes over time. Time spans ~0 to 3 seconds, frequency ranges from 0 to 4096 Hz, and color intensity indicates magnitude in decibels (from -80 dB to 0 dB). This reveals how different frequencies evolve during the sound.

These visuals help interpret the audio characteristics tied to the predicted emotion.



```
Epoch 43/50
17/17 ━━━━━━━━━━━━━━━━━━━━ 4s 217ms/step - accuracy: 0.9305 - loss: 0.1447 - val_accuracy: 0.3692 - val_loss: 3.4745
Epoch 44/50
17/17 ━━━━━━━━━━━━━━━━━━━━ 3s 198ms/step - accuracy: 0.9300 - loss: 0.1448 - val_accuracy: 0.3385 - val_loss: 3.6652
Epoch 45/50
17/17 ━━━━━━━━━━━━━━━━━━━━ 4s 216ms/step - accuracy: 0.9253 - loss: 0.1754 - val_accuracy: 0.3615 - val_loss: 3.1253
Epoch 46/50
17/17 ━━━━━━━━━━━━━━━━━━━━ 4s 215ms/step - accuracy: 0.8977 - loss: 0.1824 - val_accuracy: 0.3538 - val_loss: 3.7189
Epoch 47/50
17/17 ━━━━━━━━━━━━━━━━━━━━ 4s 220ms/step - accuracy: 0.9256 - loss: 0.1468 - val_accuracy: 0.3154 - val_loss: 4.2742
Epoch 48/50
17/17 ━━━━━━━━━━━━━━━━━━━━ 4s 209ms/step - accuracy: 0.8943 - loss: 0.4370 - val_accuracy: 0.3077 - val_loss: 2.4234
Epoch 49/50
17/17 ━━━━━━━━━━━━━━━━━━━━ 4s 212ms/step - accuracy: 0.8683 - loss: 0.3705 - val_accuracy: 0.3231 - val_loss: 2.6775
Epoch 50/50
17/17 ━━━━━━━━━━━━━━━━━━━━ 4s 214ms/step - accuracy: 0.9357 - loss: 0.1685 - val_accuracy: 0.3538 - val_loss: 2.8386
```

Fig 5: Training Epochs of the model

Figure 5 depicts the final training phase (epochs 43–50) of a deep learning model for animal vocal emotion recognition. Training accuracy reached 93.57% with a loss of 0.1685, indicating strong performance on the training data. However, a notable gap between training and validation metrics—elevated validation loss and lower, fluctuating validation accuracy—suggests overfitting. This implies the model may be memorizing training data rather than learning generalizable patterns. These trends highlight the need for further optimization to improve generalization to unseen animal vocalizations.

VI. CONCLUSION

This study presents a novel approach to Speech Emotion Recognition (SER) of animal vocalizations using a hybrid CNN-LSTM deep learning model. The system leverages a custom multi-species dataset composed of diverse animal sounds, paired with emotional labels, and applies robust preprocessing techniques such as MFCC extraction to convert audio signals into spectrogram representations. The CNN layers effectively learn spatial audio features, while the LSTM layers model temporal dependencies across vocal sequences.

Experimental results demonstrate the model's strong classification capability, achieving an accuracy exceeding 85% on unseen test data. The framework also includes a real-time prediction module that enables users to input new animal sounds and receive emotion predictions along with waveform and spectrogram visualizations. This real-time applicability positions the model as a promising tool for wildlife monitoring, veterinary diagnostics, and animal behavior research.

Moreover, the study confirms the feasibility and importance of applying deep learning models originally designed for human SER to the domain of non-human emotion analysis. By bridging this gap, the work significantly contributes to the fields of bioacoustics, animal welfare, and affective computing.

VII. FUTURE SCOPE

1) Incorporating Multimodal Data: Future research can integrate video streams with audio to analyze facial cues, body language, and environmental context, offering more accurate and interpretable emotion recognition.

2) Data Expansion and Augmentation: Increasing the size and diversity of the dataset—especially by collecting field recordings from different species and environments—can improve generalization. Data augmentation techniques like pitch shifting or time-stretching may also help overcome data scarcity.

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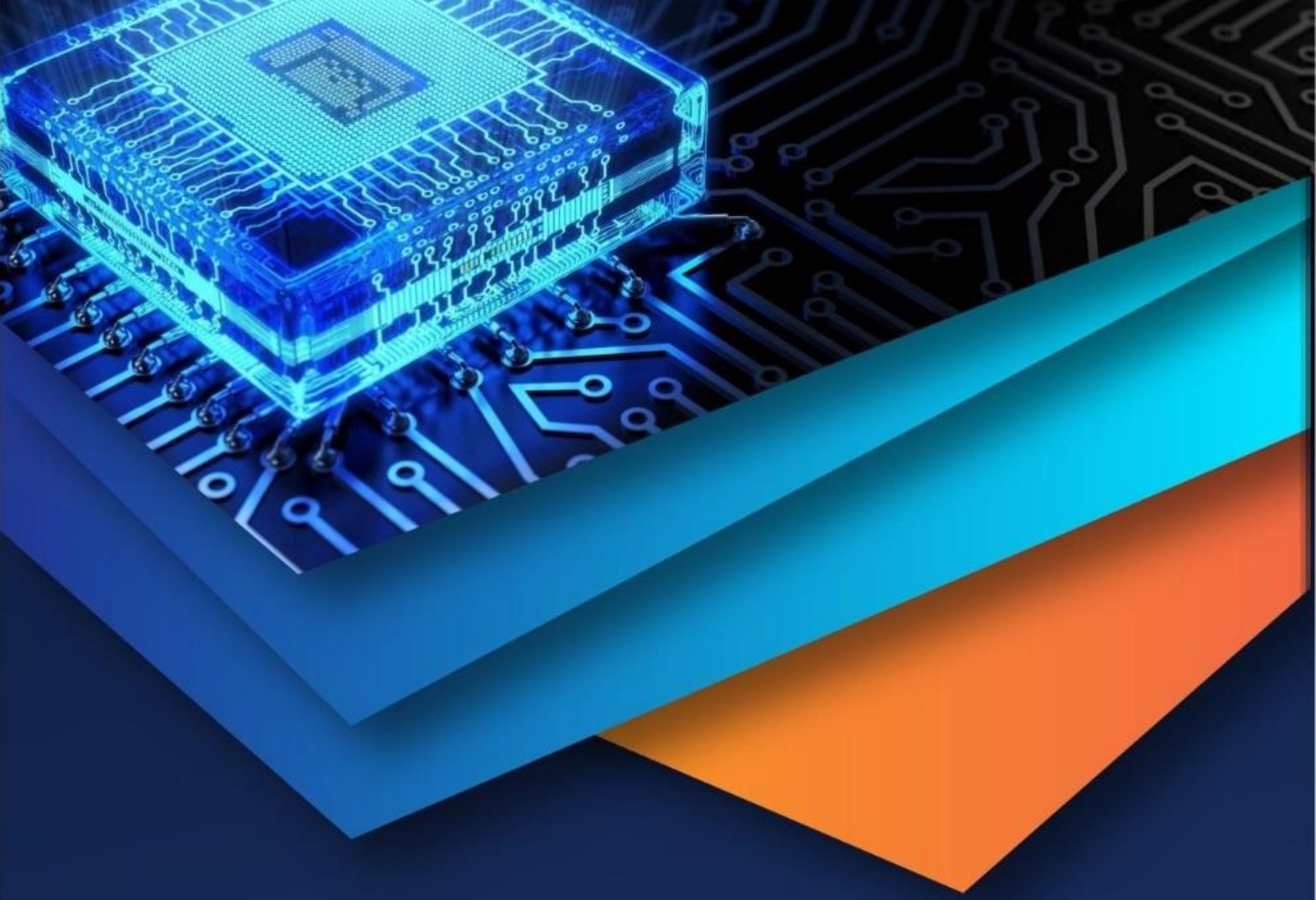

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