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CNN - Enabled Wildlife Surveillance and Monitoring System

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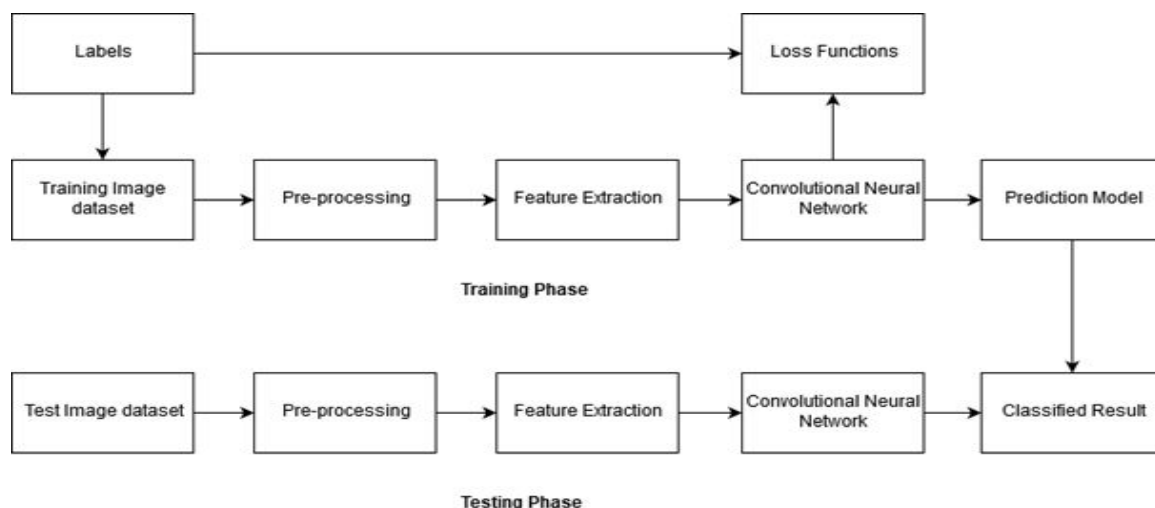
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ABSTRACT: This study uses convolutional neural networks (CNNs) to automate wildlife surveillance by classifying animal species from images. It starts with collecting and preprocessing image data through resizing, normalization, augmentation, and noise reduction. Transfer learning with models like VGG16 or ResNet is used to enhance accuracy and training efficiency. A CNN model is developed using convolutional, pooling, and fully connected layers. The model is evaluated using accuracy, precision, recall, and F1-score. Challenges like lighting variation, background clutter, and occlusion are addressed using optimization techniques. The system supports conservation efforts and suggests future improvements with real-time monitoring and object detection.

KEYWORDS: SER, Mel, MFCC, MLP, CNNLSTM.

I. INTRODUCTION

The CNN-Enabled Wildlife Surveillance and Monitoring System automates animal identification using deep learning to support wildlife research and conservation. It helps detect poaching threats, track endangered species, and monitor animal populations with high accuracy. By training CNN models on diverse datasets, the system provides reliable classification and actionable insights. It overcomes the limitations of traditional manual observation methods, which are often slow and error-prone. The platform offers a scalable, real-time solution that reduces the need for constant human involvement. Advanced CNN architectures enhance precision in classification tasks.



This makes ecological data analysis more efficient and accessible. The system empowers researchers with accurate tools for field monitoring. It also aids in making informed, data-driven conservation decisions. Overall, it bridges traditional practices with modern AI for better wildlife protection.

II. LITERATURE REVIEW

The project highlights the growing role of deep learning, especially CNNs, in wildlife monitoring. Several studies have shown CNNs outperform traditional image processing techniques in animal classification tasks. Research using pre-trained models like VGG16, ResNet, and Inception has demonstrated improved accuracy and efficiency in image recognition. Data augmentation and preprocessing methods have been found to significantly enhance model performance. Studies emphasize the importance of handling variations in lighting, background, and occlusion. Transfer learning is widely adopted to reduce training time and improve generalization. Literature also explores the integration of object detection models for real-time tracking. Many works highlight the use of drones and remote sensors for capturing wildlife data. CNN-based approaches are considered scalable and adaptable for different species and habitats. Overall, the survey establishes CNNs as a powerful tool for automated, accurate, and efficient wildlife surveillance.

III. METHODOLOGY

The methodology begins with data collection, sourcing a diverse set of wildlife images from publicly available datasets and custom field sources. These images represent various animal species across different habitats, lighting conditions, and perspectives. Proper labeling is done to ensure accurate ground truth for each image. The dataset is then split into training, validation, and testing sets. This initial step lays the foundation for building a reliable classification system. Next, the images undergo preprocessing to enhance data quality and model readiness. Steps include resizing images to a uniform dimension, normalizing pixel values, and applying noise reduction. Data augmentation techniques such as flipping, rotation, and zooming are used to increase dataset diversity. These steps help in reducing overfitting and improving generalization. The processed data is then prepared for input into the CNN model.

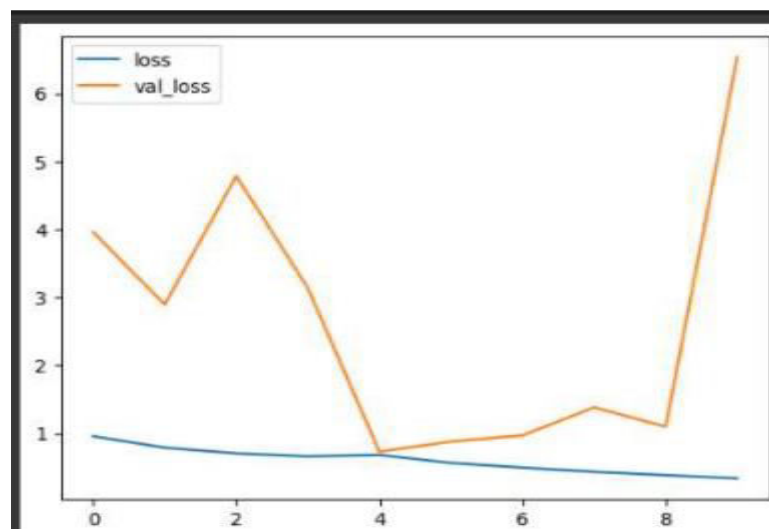


Fig 1: Loss v/s Validation Loss

A CNN architecture is developed or selected, possibly using pre-trained models like VGG16 or ResNet through transfer learning. The network includes convolutional, pooling, and fully connected layers to extract and learn features. Hyperparameters such as learning rate, batch size, and epochs are tuned to optimize training. The model is trained using

the training set and validated with the validation set. Performance is closely monitored to avoid underfitting or overfitting.

Finally, the trained model is evaluated using the testing set with metrics such as accuracy, precision, recall, and F1-score. These metrics help assess the model's ability to correctly classify animal species under varied conditions. The model's robustness is tested against images with background noise, occlusion, and lighting variations. Based on results, further fine-tuning or retraining may be conducted. The final model is then deployed as a wildlife monitoring tool for conservation applications.

IV. IMPLEMENTATION

The implementation phase begins with setting up the development environment using Python, TensorFlow, and Keras for building and training the CNN model. The preprocessed dataset is loaded and augmented using Keras' ImageDataGenerator to increase variability and robustness. A pre-trained CNN model like ResNet50 is imported and fine-tuned to adapt to the animal classification task. Custom layers are added on top of the base model to match the number of animal classes. The model is compiled using the Adam optimizer and categorical cross-entropy loss function. It is then trained using the training set while monitoring performance on the validation set.

After training, the model is evaluated on the test set to determine its accuracy, precision, recall, and F1-score. Confusion matrices and classification reports are generated to analyze class-wise performance. To improve generalization, techniques like dropout and regularization are employed during training. The final model is saved and deployed as a wildlife surveillance tool, capable of classifying animals in real-time images. A simple user interface or API is developed to allow researchers to upload images and receive predictions. This implementation bridges machine learning with conservation, offering a practical solution for automated wildlife monitoring.

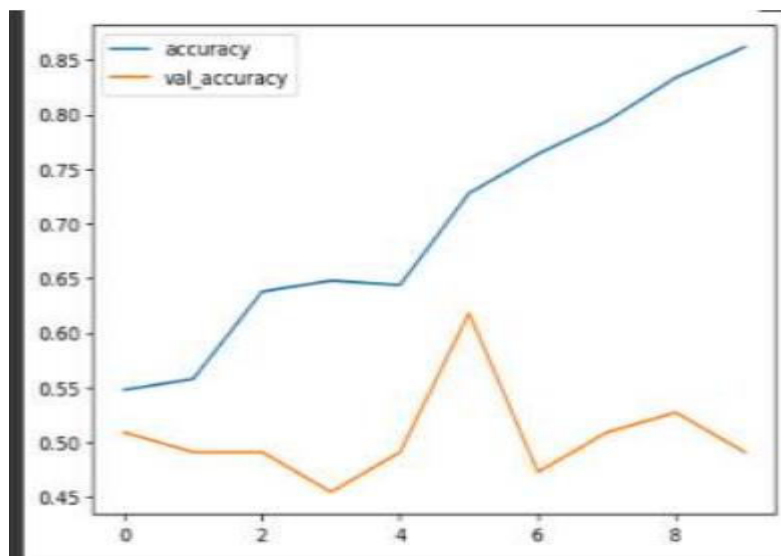


Fig 2: Accuracy v/s Validation Accuracy

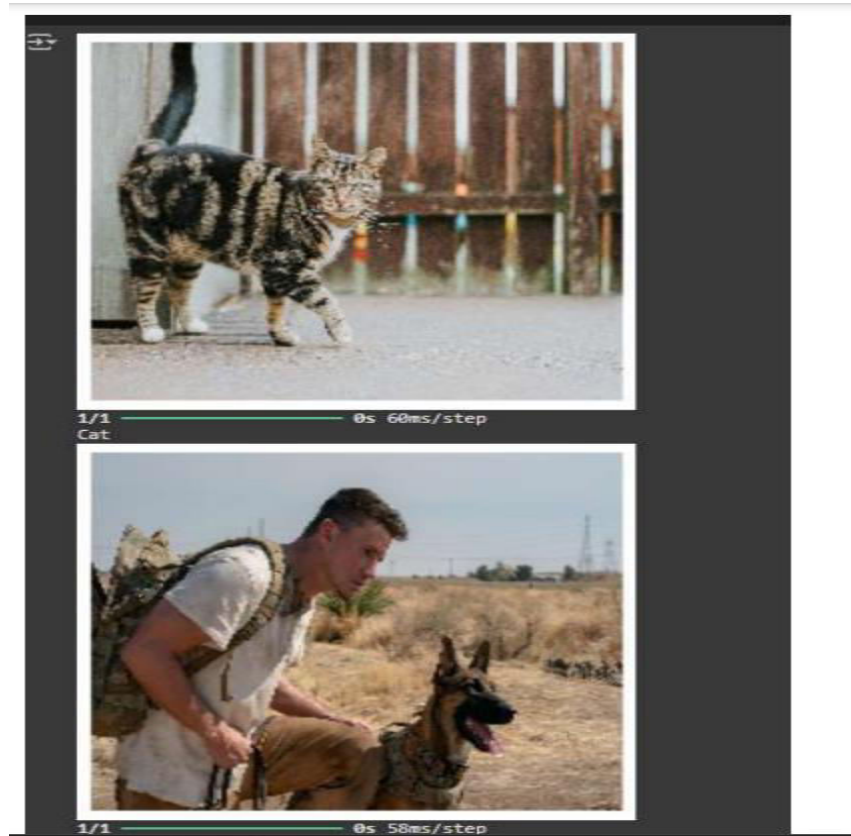
V. RESULTS AND CONCLUSION

Fig 3: Result

The proposed CNN-enabled wildlife surveillance and monitoring systems successfully achieved its objectives by automating animal identification from images. The dataset preprocessing module ensured high-quality inputs through image normalization, augmentation, and labeling. The model training and evaluation module effectively classified wildlife species with high accuracy, enabling researchers and conservationists to track animal movements and detect potential threats. Features such as real-time image processing and cloud-based storage integration enhanced the system's usability for large-scale deployment.

The project demonstrated the effectiveness of deep learning techniques, particularly CNNs, in automating wildlife surveillance and monitoring. The integration of image preprocessing techniques and transfer learning significantly improved model accuracy and generalization. The use of Flask for API deployment enabled real-time species identification, highlighting the practical applicability of the system in conservation research.

VI. LIMITATIONS AND FUTURE WORK**6.1 Enhanced Data Collection and Augmentation**

Gather extensive and varied datasets that encompass multiple languages, different accents, and a range of emotional expressions. Utilize sophisticated data augmentation methods, such as altering pitch and adding noise, to enhance the model's resilience.

6.2 Integration with Edge Computing for Faster Processing

To improve real-time processing and reduce latency, integrating edge computing with the wildlife surveillance system can significantly enhance efficiency. Instead of relying solely on cloud-based processing, edge devices such as AI-powered cameras and embedded GPUs (e.g., NVIDIA Jetson) can perform on-device animal classification and detection. This would enable faster decision-making and immediate alerts in remote areas with limited internet connectivity.

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