The Common Cuckoo (*Cuculus canorus*) is a migratory bird species known for its characteristic "cuckoo" call. This bird is widely recognized in the Netherlands and other parts of Europe as a harbinger of spring. Monitoring its population and migration patterns provides valuable insights into environmental health, as changes in its presence can indicate shifts in the ecosystem.

The objective of this project is to develop a machine learning model capable of recognizing and classifying the Common Cuckoo's call from audio recordings. By automating the detection process, researchers can efficiently monitor cuckoo populations, aiding conservation efforts and ecological studies.

Methodology

Dataset

1. **Source**:
    - audio data was collected from open-source repository Xeno-Canto.
    - two audio categories were prepared:
        - Cuckoo calls.
        - Non-cuckoo calls (e.g., other bird species and background noises).
2. **Preprocessing**:
    - **Segmentation**: audio files were split into 3-second segments.
    - **Augmentation**: noise was added to simulate challenging environmental conditions:
        - white noise (Signal-to-Noise Ratio = 30).
        - spectrogram distortions and overlaps with non-cuckoo sounds.
    - **Feature Extraction**: Mel spectrograms were generated using the librosa library. Each spectrogram was resized to 128x128 pixels to suit the input size of the neural network.

Model Architecture

1. **Choice of Algorithm**:
    - A MobileNet architecture was selected for its efficiency and lightweight design, which is particularly advantageous for on-device and real-time applications.
2. **Transfer Learning**:
    - MobileNet was pre-trained on the ImageNet dataset.
    - The final 20 layers were fine-tuned for cuckoo call classification while retaining general feature extraction capabilities.

3. **Optimization**:
    - **Regularization**:
        - Dropout layers were added to reduce overfitting.
    - **Early Stopping**:
        - Training stopped automatically when the validation loss plateaued.
    - **Learning Rate Scheduling**:
        - The learning rate was reduced upon validation performance stagnation.

Training and Validation

- The dataset was divided as follows:
    - **Training Set**: 80%.
    - **Validation Set**: 20%.
- A total of 400 samples of noisy cuckoo calls and 400 samples of noisy non-cuckoo calls were used.

Results

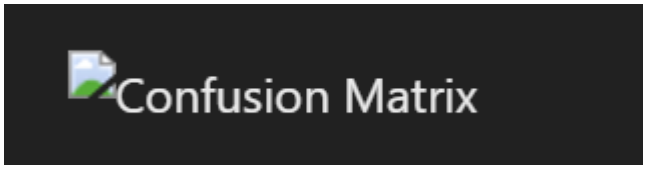
Model Performance

The following evaluation metrics were used:

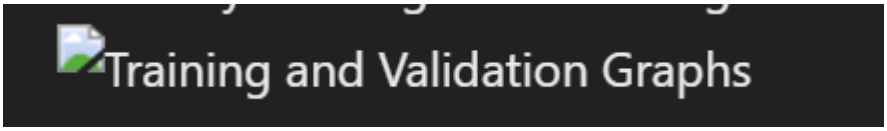
- **Accuracy**: A measure of correct predictions over all predictions.
- **Precision, Recall, F1-Score**: Indicators of the model's balance in handling both classes.
- **Confusion Matrix**: To visualize misclassifications.

1. **Performance Metrics**:
    - **Precision**:
        - Cuckoo Noisy: 0.93
        - Non-Cuckoo Noisy: 0.90
    - **Recall**:
        - Cuckoo Noisy: 0.90
        - Non-Cuckoo Noisy: 0.93
    - **F1-Score**: 0.91 (Macro Average)
    - **Overall Accuracy**: 91%.

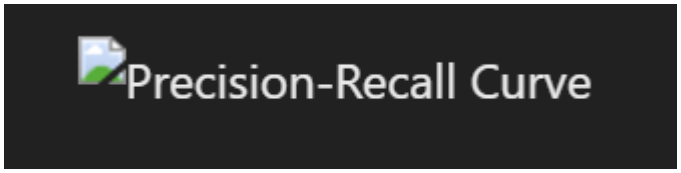
2. **Visualizations**:
    - **Confusion Matrix**: As shown below, the confusion matrix demonstrates the balance of predictions across the two classes:



    - **Training and Validation Performance**: The loss and accuracy graphs below indicate that the model successfully avoided overfitting:
        - Loss steadily decreased for both training and validation sets.
        - Accuracy converged for training and validation sets, reaching 91%:



    - **Precision-Recall Curve**: The Precision-Recall Curve with an Area Under Curve (AUC) of 0.89 shows the model's performance in differentiating the two classes:
    -



Discussion

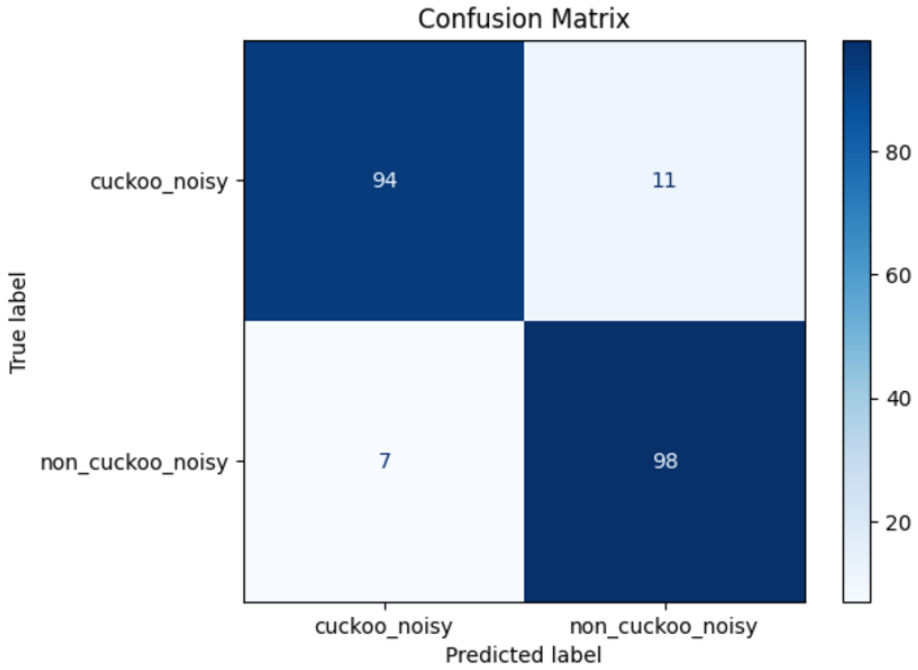
1. **Insights**:
    - The model successfully learned the distinctive features of the cuckoo's call, even under challenging noisy conditions.
    - MobileNet's transfer learning capability made it efficient in feature extraction and accurate classification.
2. **Challenges**:
    - Adding noisy data introduced misclassifications, which revealed the model's vulnerability to overlapping audio conditions.
    - Despite the high accuracy, real-world conditions may require more diverse datasets to account for environmental variability.
3. **Future Work**:
    - **Dataset Expansion**:
        - Include more recordings under varying environmental conditions and overlapping bird calls.
    - **Testing on Unseen Data**:

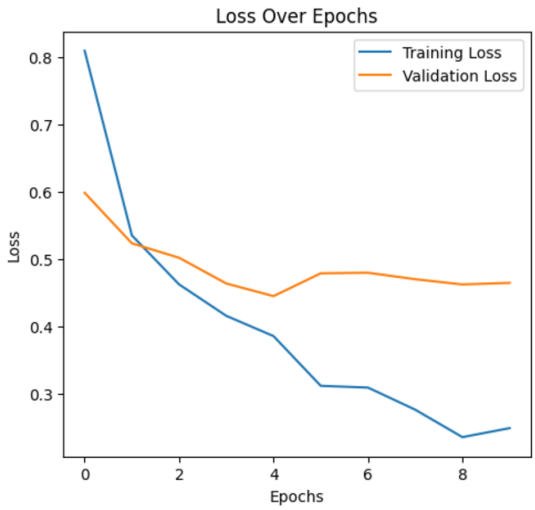
- Evaluate the model on a separate test set to ensure robustness.

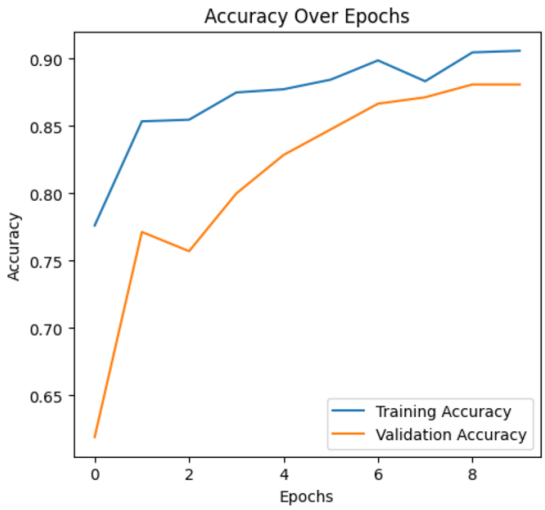
- **Deployment**:
  - Integrate the trained model into mobile or edge devices for real-time cuckoo call detection.

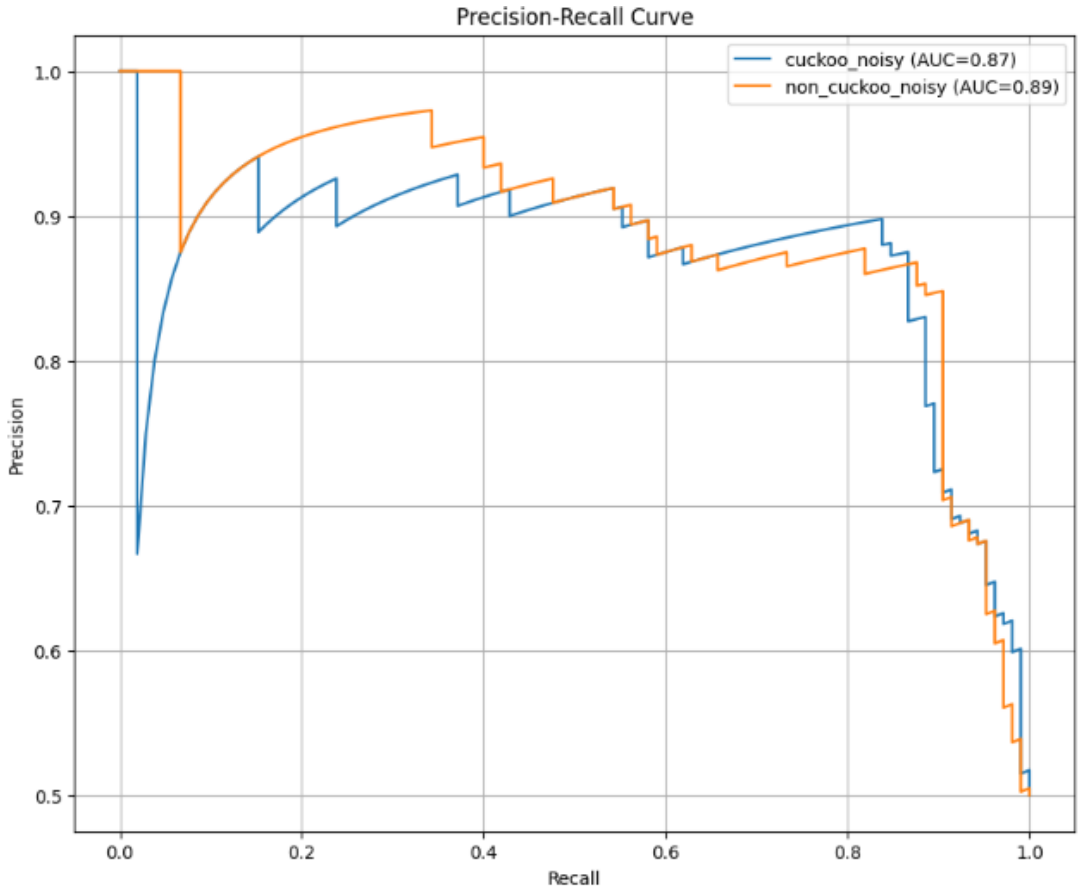
4. **Broader Applications**:
   - This approach can be extended to other species for biodiversity monitoring and conservation research. It could also support soundscape ecology studies, providing tools for large-scale environmental monitoring.

	precision	recall	f1-score	support
cuckoo_noisy	0.93	0.90	0.91	105
non_cuckoo_noisy	0.90	0.93	0.92	105
accuracy			0.91	210
macro avg	0.91	0.91	0.91	210
weighted avg	0.91	0.91	0.91	210




Loss Over Epochs
Training Loss
Validation Loss
Loss
Epochs
0.8
0.7
0.6
0.5
0.4
0.3
0
2
4
6
8


Accuracy Over Epochs
Training Accuracy
Validation Accuracy
Accuracy
Epochs
0.90
0.85
0.80
0.75
0.70
0.65
0
2
4
6
8


Precision-Recall Curve
cuckoo_noisy (AUC=0.87)
non_cuckoo_noisy (AUC=0.89)
Precision
Recall
1.0
0.9
0.8
0.7
0.6
0.5
0.0
0.2
0.4
0.6
0.8
1.0