

Chloris

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Table of Contents

Title	1
<u>Problem Statement</u>	2
<u>Approach</u>	2
<u>Software & Dependency Outline</u>	2-3
<u>Evaluation</u>	3-5
<u>Conclusion</u>	6-7
<u>References</u>	7

Problem Statement

For casual hikers, beginner bird spotters, or just for the curious mind, identifying birds and bird species might be a difficult task without prior training or data. What Chloris aims to solve is this issue. With over 85,000 samples of 525 species, Chloris uses machine learning and convoluted neural networks to bring the knowledge and experience of an ornithologist to the tip of your finger. Further, Chloris allows, with use of geolocation, to calculate the probability of certain bird sightings.

Approach

Chloris uses a Resnet 50 (Residual Neural Network of 50 layers) fitted to the [525-Bird-Species dataset](#) (Previously only 100 species). My Resnet model allows for efficient generalization and convergence with specific parameters and back propagation. It also uses a One Class Support Vector Machine (OC-SVM) to fit [FeederWatch](#) sightings, and calculates probability and possibility of a new sighting with the use of distance equations and inlier/outlier algorithms.

Software & Dependency Outline

The Chloris app have 3 main components, front end, api, and backend scripts/models, the structure of the components are as follow

- Front end
 - Expo Go and NodeJS
 - Written in HTML, CSS, and Javascript
- API
 - Fast Api
 - Written in Python
- Backend Scripts and Models
 - Tensorflow, scikit-learn, and pandas
 - Written in Python, mainly jupyter notebook on google colab
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The datasets for the models, as mentioned in the approach, are from the Hugging Face dataset library and the FeederWatch website

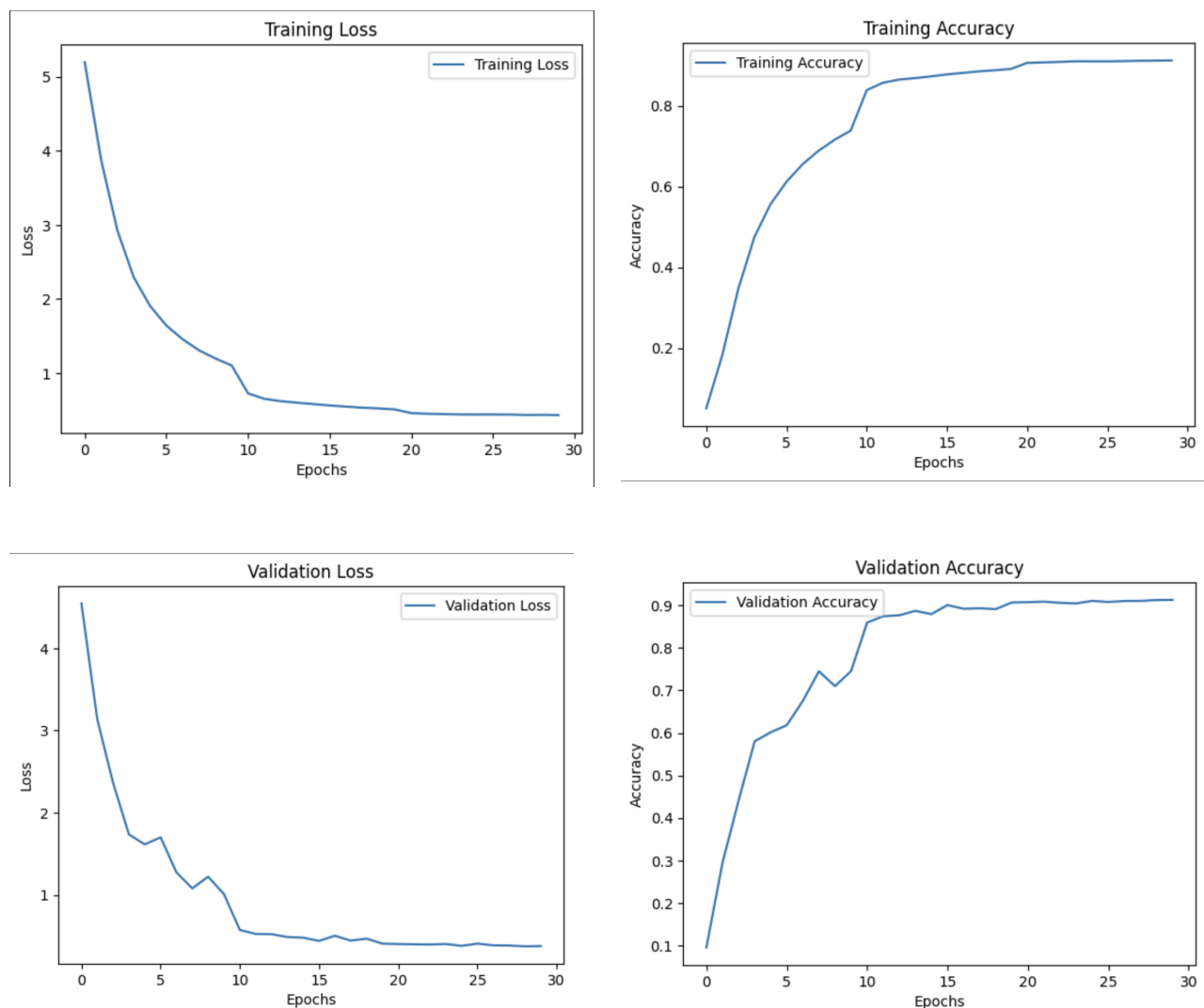
- <https://huggingface.co/chriamue/bird-species-classifier>
- <https://feederwatch.org/explore/raw-dataset-requests/>

The libraries used can be found on the ReadMe file on the github repository as it is extensive

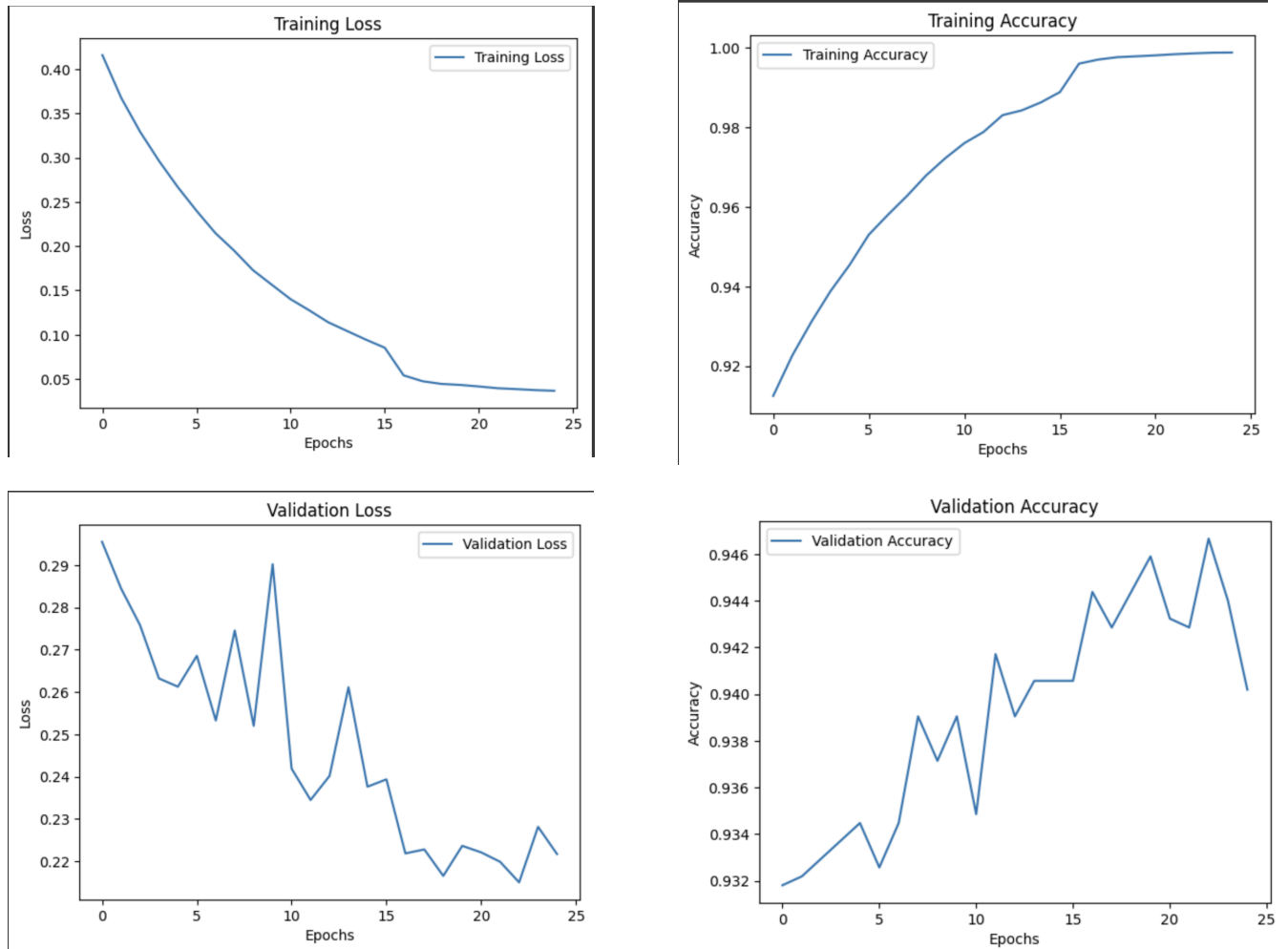
Evaluation

Substantial evaluation was applied to the models post training and will be shown below.

Resnet50

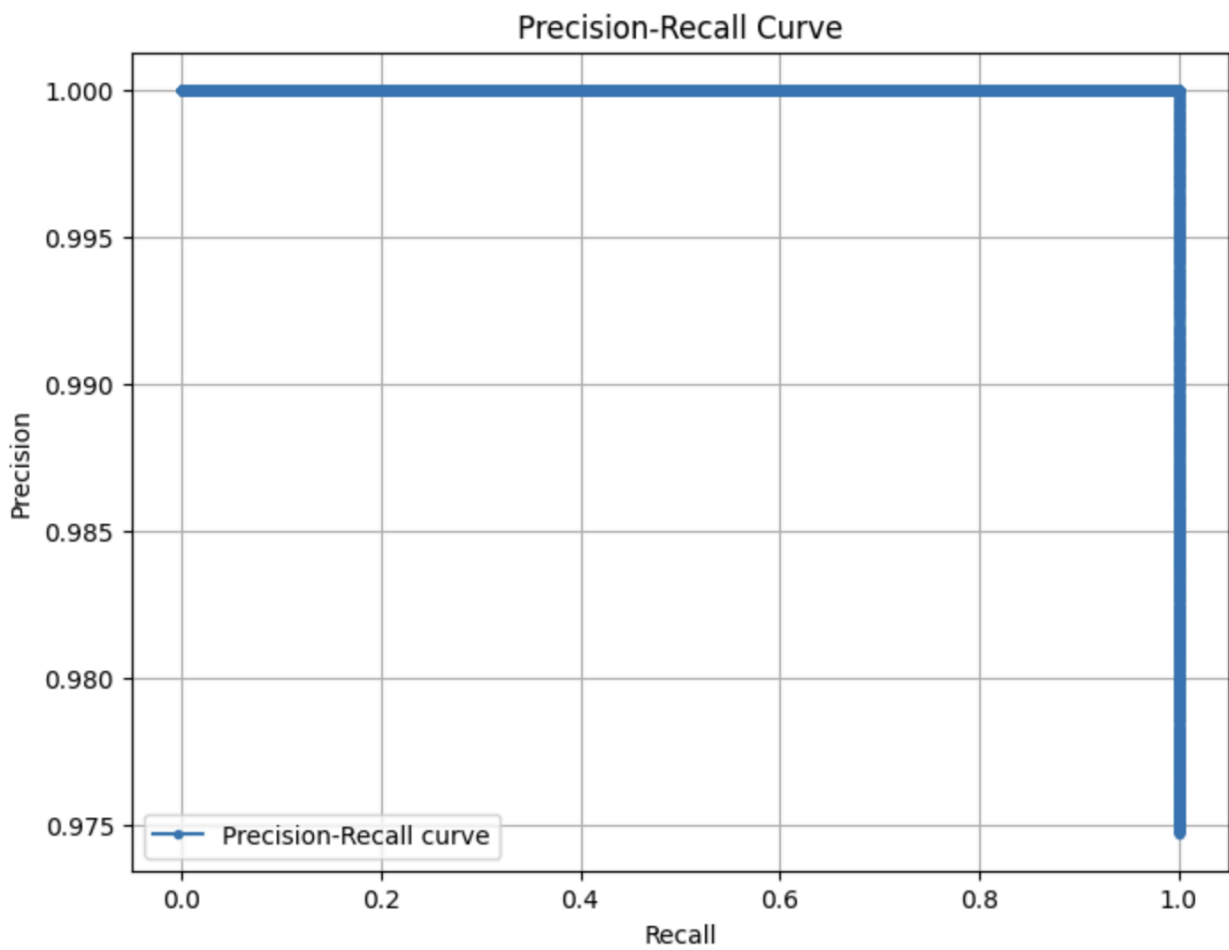


Resnet50 Cont



As shown above the loss achieved after 55 epochs was sub 0.25 from an initial loss of 5.60, the accuracy achieved on the training set was a 0.99 and for the validation set was a 0.94, as you can see, though overfitting or underfitting were never an issue there was some instability towards the end of the training. This performance was achieved with learning rate schedulers, optimizers, and loss functions, all which can be further read about in the code report.

OC-SVM



For the OC-SVM, a precision accuracy score of 0.99 was achieved and a perfect Precision Recall graph was produced. Though I never found irregularities, this recall graph could imply overfitting or overconfidence of the model.

Conclusion

Chloris sets out to address the challenge of bird species identification for casual hikers, beginner bird spotters, and those with a curious interest. Through the utilization of machine learning techniques, Chloris endeavors to provide users with the expertise and insights of an ornithologist at their fingertips. With a comprehensive dataset comprising over 85,000 samples across 525 bird species, Chloris employs a Resnet 50 neural network and One Class Support Vector Machine (OC-SVM) to deliver accurate predictions and probabilities of bird sightings.

Main Lessons Learned:

1. **Model Performance:** Chloris demonstrates remarkable performance, with the Resnet 50 model achieving a training accuracy of 0.99 and a validation accuracy of 0.94. The OC-SVM model achieves a precision accuracy score of 0.99. However, indications of potential overfitting or overconfidence in the OC-SVM model were observed, as suggested by the Precision-Recall graph.
2. **Stability and Optimization:** While overfitting or underfitting were not significant concerns during training, some instability was noted towards the latter stages of Resnet 50 training. This underscores the importance of optimizing hyperparameters, learning rate schedulers, optimizers, and loss functions to enhance model stability and convergence.
3. **Data Sources:** Leveraging datasets from reputable sources such as the Hugging Face dataset library and FeederWatch website ensures the quality and diversity of the data used for training and evaluation. This contributes to the robustness and generalization capabilities of the models.

Ideas for Improvement:

1. **Addressing Model Confidence:** Further investigation into the potential overconfidence or overfitting of the OC-SVM model is warranted. Fine-tuning the model parameters or exploring alternative anomaly detection techniques may help mitigate this issue.
2. **Enhancing Stability:** Continuously refining the training process by experimenting with different architectures, regularization techniques, and training strategies can improve the stability and convergence of the models.

3. Expanding Dataset and Features: Increasing the diversity and volume of the dataset, particularly by incorporating more bird species and geographical regions, can enhance the model's ability to generalize to a wider range of scenarios.
4. User Experience: Enhancements to the user interface, such as incorporating interactive features, providing informative feedback on bird sightings, and integrating additional functionalities like bird call recognition, can enrich the user experience and make Chloris more engaging and user-friendly.

References

<https://feederwatch.org/explore/raw-dataset-requests/>

<https://www.kaggle.com/datasets/gpiosenska/100-bird-species>

<https://www.baeldung.com/cs/one-class-svm>

<https://scikit-learn.org/stable/modules/svm.html#svm-outlier-detection>

<https://www.tensorflow.org/tutorials/images/cnn>

<https://www.datacamp.com/tutorial/complete-guide-data-augmentation>

https://www.youtube.com/watch?v=GWt6Fu05voI&ab_channel=YannicKilcher

<https://arxiv.org/abs/1512.03385>