Advanced Military Aircraft Detection and Classification Using Convolutional Neural Networks (CNNs)

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Abstract

In recent years, the detection and classification of military aircraft have become critical components of modern defense systems. This project proposes the development of a deep learning-based detection model using Convolutional Neural Networks to identify military aircraft in various environments and conditions. Specifically, this project will be implementing two different models, ResNet50 and EfficientNetV2B0 to see which model gives us better results. The two proposed models will be trained using a large dataset of military aircraft images, consisting of more than 60000 images of various aircraft, incorporating different perspectives, altitudes, and weather conditions to ensure robustness. In addition to model development, the project explores the challenges associated with dataset labeling, augmentation, and preprocessing, which are crucial in improving detection accuracy. The model will be evaluated using metrics like accuracy and loss, as well as using techniques such as data augmentation, max pooling, and batch normalization to reduce the chances of overfitting and increasing the efficiency of the models.

Background

The accurate classification of military aircraft is key for enhancing defense capabilities, as it allows for a more precise understanding of the type and potential threat level posed by different aircraft. In situations where all aircraft in the dataset are military, the task becomes one of distinguishing between various models and types, which could be critical in defense operations. For example, the ability to quickly differentiate between fighter jets, bombers, reconnaissance aircraft, or transport planes can provide decision-makers with vital information about the nature of an airborne operation.

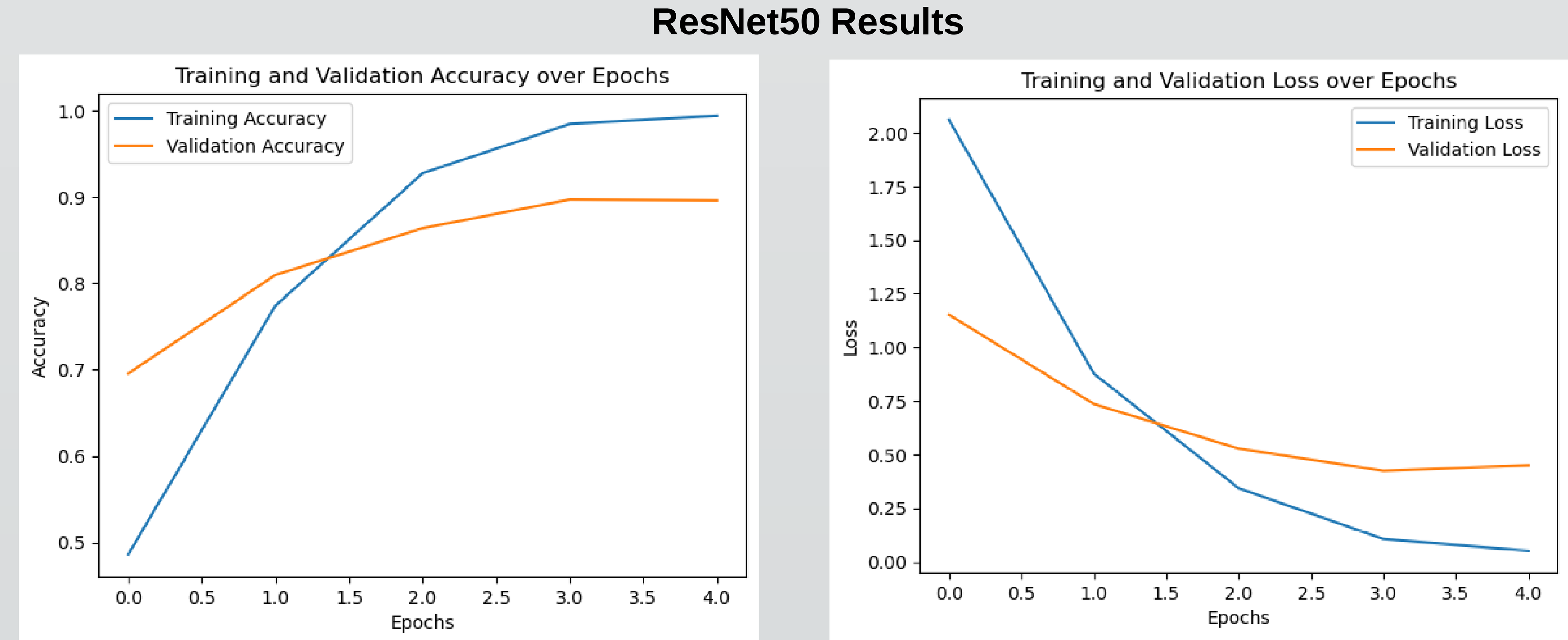
This classification can also improve situational awareness in real-time combat scenarios. By applying CNNs to this task, we can enhance the speed and accuracy of identifying the exact type of aircraft entering protected airspace, helping military personnel assess the potential threat and determine an appropriate response. Additionally, this technology can assist in training autonomous systems, such as unmanned defense drones or automated surveillance tools, to accurately recognize and respond to different types of military aircraft without human intervention.

Methods

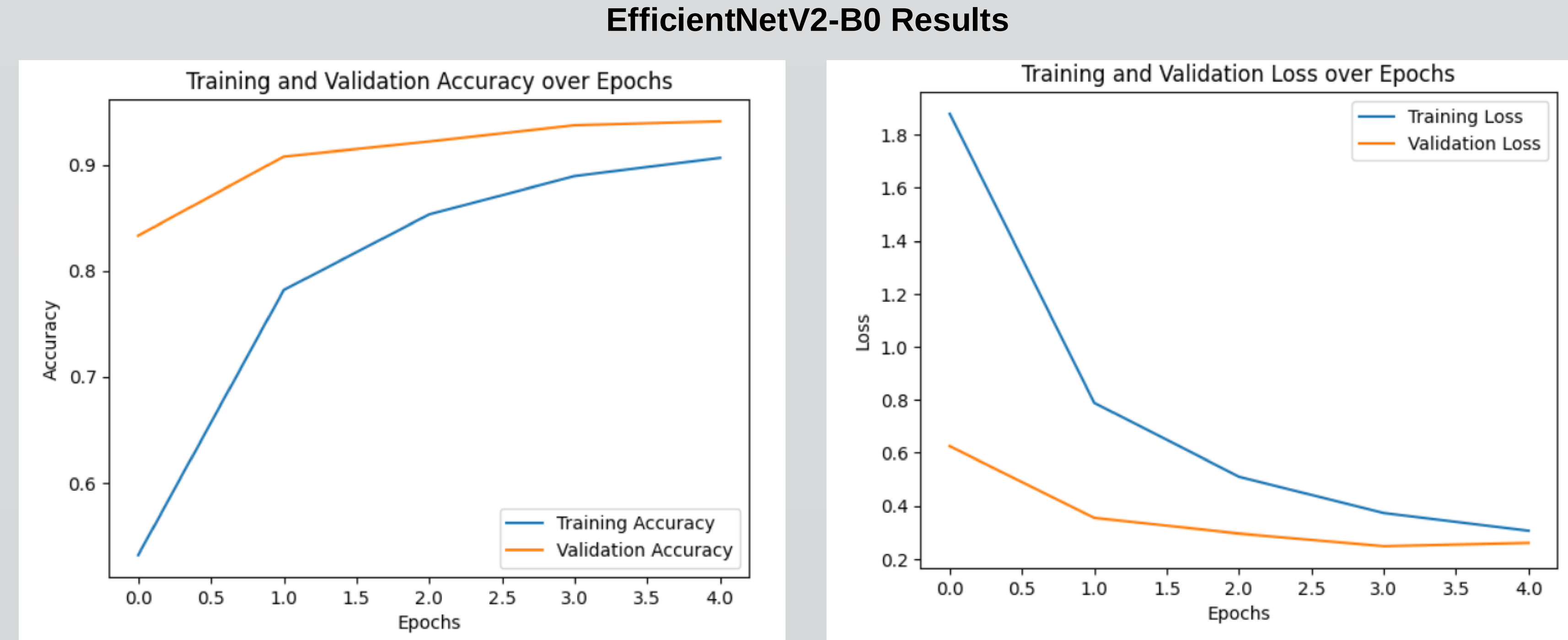
For the EfficientNetV2B0 model, we set the foundation by using the base model, pre-training it using ImageNet, setting its input shape as the full image size that was set by splitting the data into the training and validation datasets, and removing its top layers to allow more flexibility and reduces computational cost. All of its layers are initially set to be frozen, so that it's able to retain the weights from its ImageNet pre-training, but we then allow the last 30 layers of the model to be trained so that it can adjust itself to our dataset, allowing the model to retain important information from ImageNet. A GlobalMaxPooling2D layer is then applied, reducing the spatial dimensions of the feature maps to a single vector, which reserves important pooling information, followed by a Batch Normalization and output layer which utilizes the SoftMax activation function.

For the ResNet50 model, we used the base model and set it up similarly like the EfficientNetV2B0 model, but also adding data augmentation which helps it to reduce overfitting and makes it more robust with new data, adding a convolutional layer with batch normalization, as well as adding a GlobalAveragePooling2D layer, which calculates the average value of each feature map across its entire spatial dimensions.

ResNet50 Results



EfficientNetV2-B0 Results



Results

Models	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss	Time per Epoch
ResNet-50 (Batch Size 16)	96.7%	0.14	88.3%	0.88	798 seconds
ResNet-50 (Batch Size 32)	87.8%	0.47	75.7%	0.52	165 seconds
ResNet-50 (Batch Size 48)	99.3%	0.059	91%	0.38	741 seconds
EfficientNetV2B0	94.3%	0.19	93.1%	0.29	262 seconds

Conclusion

In conclusion, while both models successfully learned from the dataset, EfficientNetV2B0 emerged as the more efficient model overall. Although ResNet50 has shorter individual epoch times, it would require additional epochs to reach performance comparable to EfficientNetV2B0. This demonstrates that EfficientNetV2B0 is not only more accurate but also achieves these results with fewer training resources, making it preferable when both time and computational cost are considerations. For applications requiring faster training iterations or limited resources, ResNet50 could still be a viable choice, but at the expense of lower accuracy and higher validation loss without extended training. Ultimately, EfficientNetV2B0's balance of accuracy and efficiency makes it the more effective model for this dataset.

Future Direction

Future work will expand the dataset to include more diverse aircraft models, environmental conditions, and real-time scenarios to enhance model generalization and robustness. Additionally, efforts will focus on further optimizing the model for reduced overfitting, higher accuracy and quality. Leveraging transfer learning, we aim to adapt these models for other defense-related tasks, such as identifying drones or ground vehicles, thereby broadening their applicability and impact.

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