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AERONET: Design and Evaluation of Systematic Experimental Frameworks for Custom CNN-Based Military Aircraft Recognition in High-Resolution Satellite Imagery

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Abstract

High-resolution satellite images play an important role in defense monitoring, information gathering through reconnaissance and strategic intelligence systems. This research proposes a framework based on deep learning to automatically classify military aircraft using annotated satellite image datasets that contain horizontal bounding box data. The preprocessing steps for these datasets included removing undesired objects, cutting out selected images from the original image file, adding borders, enlarging images, reducing the depth of color in the pixels for each image so they were the same size and had the same amount of colors and creating one-hot encoded labels for each of the images. Three custom convolutional neural networks are developed using hyperparameter tuning with KerasTuner and Adam optimization, namely Custom CNN_1, Custom CNN_2 and Custom CNN_3. Different train-test split ratios are used, which were 90:10, 85:15, 80:20, 75:25, 70:30, 65:35 and 60:40. The final evaluation criteria for each of the models are accuracy, precision, recall and F1-score. Of the three Custom CNN models, Custom CNN_1 produced an average accuracy of 92.95% and had the highest overall accuracy for all of the experiments, while Custom CNN_3 had an individual maximum accuracy of 94.11%. The results of this research support that the custom CNN-based framework provides the necessary processes to accurately extract the spatial features that can discriminate between objects in high-resolution satellite imagery for the purposes of classifying military aircraft.

Keywords: Machine Learning, Remote Sensing, Military Aircraft, Satellite Imagery, Military Aircraft Detection, Geospatial Intelligence

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1. INTRODUCTION

The identification of military aircraft in high-resolution satellite images (HRSMs) has become an increasingly important part of modern remote sensing and defense-intelligence systems [1]. Due to the many variables in scale, orientation, and background of a variety of aircraft, a robust automated analysis framework is necessary. The rise of machine learning (ML) and deep learning (DL) via convolutional neural networks and object-detection frameworks has greatly enhanced detection accuracy and speed in real time [2]. Using these technologies provides the ability to create hierarchical features from complex spatial data to more accurately identify and classify military assets. In addition, challenges still exist, including limited datasets, occlusion, low resolution and further research will be needed to develop optimized deep-learning pipelines for operational deployment [3].

2. LIMITATIONS OF TRADITIONAL SYSTEMS

High-resolution satellite imagery contains many traditional methods of classifying military aircraft based on handcrafted feature extraction and rule-based computer vision are limited in their ability to adapt to the high intra-class variation, partial occlusions, and background clutter that are common in remote sensing data. This is mainly because they are dependent on manually developed feature descriptors such as SIFT or HOG, which limit their ability to adapt to different imaging conditions [1][2]. In addition, conventional machine learning classifiers do not scale or provide robustness to large dimensional geospatial datasets. When tested against variations in luminosity, resolution and angle of viewing, they also experienced decreased performance, making them ill-suited for real-time

or operational defense applications, while compared to modern deep learning approaches [4][5].

3. MOTIVATION FOR WORK

Rapidly evolving high-resolution satellite imaging technologies are giving way to incredible opportunities for the use of machine learning and deep learning methods in the automated detection and classification of military aircraft from satellite imagery. Conventional techniques and dependencies on manual and algorithmic processes alone are not enough due to increased complexity of data; therefore, it is necessary to develop more adaptable and scalable intelligent systems for the purposes of defense intelligence applications. Improved accuracy, robustness, and decision support will result from the implementation of this intelligent technology within complex spatial environments characterized by varying resolutions and occluded targets, consequently improving situational awareness and operational efficiencies in contemporary defense systems architecture.

4. AIM AND OBJECTIVES OF THE STUDY

The main aim of this research is to build and test an effective system for classifying military aircraft in high-resolution satellite images through deep learning algorithms. To achieve this, we will utilize advanced techniques for preparing images for analysis in order to improve data quality, explore various data splitting methods for appropriate testing, and complete comparative evaluations of each of the custom deep learning models created. The objective is also to evaluate the classification results according to different spatial resolutions and other imaging factors that impact performance.

5. CONTRIBUTION OF THIS WORK

This research contributes a comprehensive approach to classifying military aircraft in high-resolution satellite images using deep learning method. The major contributions presented here include a proper implementation of sophisticated preprocessing methods to enhance data quality and evaluation of different ways of splitting training sets for dataset to verify generalization of classifiers. A thorough comparison between classical and modern machine learning and deep learning architectures and performance evaluations using a variety of conditions to identify optimal parameter configurations for robust and accurate geospatial object classification tasks.

6. LITERATURE REVIEW

6.1 Related Works

Table 1. Comparative Analysis of Existing Techniques and Methodologies

Author	Year	Technology Used	Performance
Alganci U. et al. [1]	2020	YOLOv3, SSD, Faster R-CNN	Accuracy 88–93%
Tahir A. et al. [4]	2021	YOLO framework	Accuracy 85–92%
Azam B. et al. [5]	2022	Faster R-CNN, YOLO, ResNet backbones	mAP up to 92%
Liu Z., et al. [6]	2023	YOLO-based detection + classification	mAP 90%
Patel K., et al. [7]	2022	CNN, Faster R-CNN	Accuracy 89–94%
Pritt M., Chern G. [8]	2020	CNN ensemble + metadata fusion	Accuracy 83%
Chen X. et al. [9]	2024	YOLO architecture with attention mechanisms	mAP –95%
El Ghazouali S. et al. [10]	2024	YOLOv5, YOLOv8, Faster R-CNN, DETR	YOLOv5 mAP 94%
Zhou F. et al. [11]	2023	YOLOv5 + Transformer + ConvNeXt backbone	Accuracy 93%
Guo X., Xu B. [12]	2024	YOLOv8	mAP 94%
Singla J. et al. [13]	2024	Mask R-CNN, YOLO frameworks	Accuracy 94%
Radionov Y.D. et al. [14]	2024	CNN + contour-based segmentation	Accuracy 90%

6.2 Identified Research Gaps

Although great strides have been made regarding the use of deep learning to classify military aircraft and other objects located in high-resolution satellite images, there remain many areas of research that have not yet been addressed. Many studies of military aircraft classification via high-resolution satellite imagery [1] have been based on either the YOLO or Faster R-CNN architectures [5][6][10], and there has been little investigation into how hybrid and ensemble learning techniques could improve the accuracy of the classifications [3][4]. Many of the classification models test accuracy based on mAP without adequately evaluating model performance under real-world conditions such as occlusion, atmospheric distortion and domain shift. In addition, while many of the studies mentioned above utilized traditional benchmarking datasets, there is an inadequate amount of research on utilizing diverse real-

world operational satellite data [11][14]. There has also been no systematic evaluation of data preprocessing methods or dataset splitting techniques among the many studies performed to date. Finally, there is insufficient research into explainability and model interpretability, both of which are necessary to support reliable decision making when using these classifiers in defence applications [12]. In image-classification applications, deep-learning performance depends not only on the selected network architecture but also on annotation quality, dataset characteristics, and appropriate validation procedures. Reviews of CNN- and YOLO-based image analysis have also emphasized the importance of external validation and transparent model evaluation [15]. These considerations are relevant to the present study because aircraft classification performance should be evaluated for its generalizability beyond a single dataset and a particular train-test split.

7. METHODOLOGY

7.1 Dataset Description

The Military Aircraft Detection Dataset [16] is designed as a high-resolution satellite imagery dataset for fine-grained object detection and classification, containing data on 101 military aircraft types. The dataset contains images annotated according to the PASCAL VOC standard, which provides bounding box coordinates, class labels, and some additional image metadata like width and height. Military aircrafts included in this dataset are not limited to but do consist of fighter aircraft, bomber aircraft, transport and equipment aircraft, unmanned aerial vehicles (UAVs), and helicopters. Although the variants are visually similar, they have been combined into one class for ease-of-use in training machine learning and deep learning models. Within each dataset folder, all annotated categories are organized into three separate folders, dataset consists of the images with the corresponding CSV annotations, crop consist of the corresponding object-level cropped images to be classified by aircraft type, and annotated samples consist of visual examples of the bounding box annotations.

7.2 Experimental Setup

The environment consisted of a high-performance computing system running on Windows 11. It had one Intel i7 CPU, 32 GB of RAM and one NVIDIA GeForce RTX 3080 GPU. The CUDA and cuDNN libraries were used to enable GPU acceleration while developing both proposed models using Python version 3.10, TensorFlow 2.x and the Keras deep-learning framework to improve training and estimation efficiency. A high-speed solid-state drive (SSD) was utilized to help minimize the delay of accessing data from disk and optimize all processes related to preparing or storing data. This configuration allowed for the efficient processing of large satellite image datasets and improved the rate at which models converged during experimentation and evaluation activities.



Fig. 1. Illustrative Image from Military Aircraft Detection Dataset [15] showcasing different classes with bounding boxes.

7.3 Data Pre-Processing

The dataset is first parsed from XML annotations using the PASCAL VOC format to extract class labels and bounding box coordinates $(x_{min}, y_{min}, x_{max}, y_{max})$. Each image $I \in \mathbb{R}^{H \times W \times 3}$ is filtered to ensure RGB consistency and corresponding regions of interest (ROI) are generated via cropping. For each object, width $w = |x_{max} - x_{min}|$ and height $h = |y_{max} - y_{min}|$ are computed. Cropped images are padded to square dimensions using $S = \max(w, h)$, followed by resizing to 64×64 . Pixel normalization is performed as $I' = I/255$. Labels are encoded using one-hot encoding, producing $y \in \{0, 1\}^C$ for $C = 101$ classes. The dataset is then split into training and testing sets using 90:10, 85:15, 80:20, 75:25, 70:30, 65:35 and 60:40 ratios.



Fig. 2. Illustration of pre-processed images after cropping, resizing, normalization and one-hot encoding.

7.4 Proposed Pipeline

The proposed pipeline for military aircraft classification in high-resolution satellite imagery integrates data preprocessing, feature learning, and multi-model CNN-based classification. Initially, input images $X \in \mathbb{R}^{H \times W \times 3}$ are annotated using PASCAL VOC XML format, where each object is defined by bounding box coordinates $b = (x_{\min}, y_{\min}, x_{\max}, y_{\max})$ and class label $c \in \{1, 2, \dots, 101\}$. Object regions are cropped, and spatial dimensions are computed as $w = |x_{\max} - x_{\min}|$ and $h = |y_{\max} - y_{\min}|$. Each ROI is padded using $S = \max(w, h)$ and resized to 64×64 . Pixel normalization is applied as $X' = X/255$. Labels are encoded using one-hot representation $y \in \{0, 1\}^C$, where $C = 101$.

The dataset is split into training and testing sets with ratios of 90:10, 85:15, 80:20, 75:25, 70:30, 65:35 and 60:40. Three CNN architectures are implemented: a baseline model, a moderately deep CNN with $k \in [1, 3]$ convolutional layers, and an enhanced CNN with extended dense units $U \in [128, 1024]$ and dropout $p \in [0.1, 0.5]$. All models utilize ReLU activation $f(x) = \max(0, x)$, softmax output,

$$\hat{y}_c = \frac{e^{z_c}}{\sum_{j=1}^C e^{z_j}}$$

and categorical cross-entropy loss

$$L = - \sum y \log(\hat{y})$$

Optimization is performed using Adam with learning rate $\eta \in \{10^{-3}, 10^{-4}\}$. Hyperparameter tuning is applied to deeper architectures to enhance generalization and classification accuracy across 101 aircraft categories.

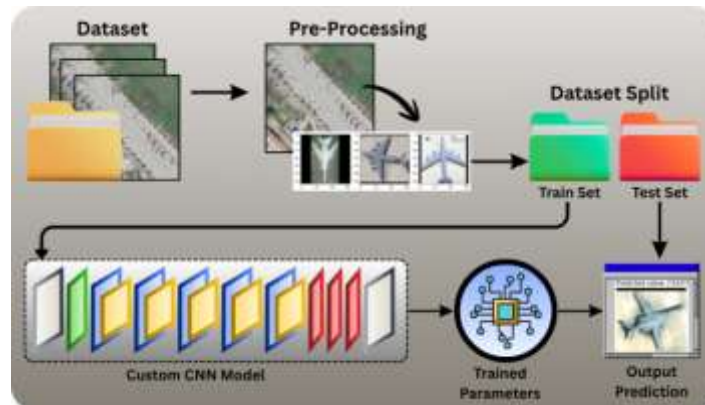


Fig. 3. Block diagram of the proposed Military Aircraft detection pipeline

7.5 Models Utilized

The proposed framework is a new way to classify military aircraft from very high-resolution satellites, using a pipeline of three stages of a convolutional neural network (CNN). Our proposed framework normalizes all input as scale them to a range between 0 and 1. First, designed the model to serve as a baseline. The initial Model is comprised of a Conv2D layer with 64 filters of size 3×3 , an AveragePooling2D layer, and a dense network classifier. The second Model extended the feature extraction process by using $L \in [1, 3]$ convolutional layers to extract features in a set of filters of space and then using pooling operations to downscale these features. The third Model integrated some form of hyperparameter optimization as Keras Tuner to tune the number of dense units in the network, the dropout probability in the network, and the learning rate of the Adam Optimizer used to converge parameters. Lastly, employed two models using softmax activation, output layer activation and categorical cross-entropy loss function in order to classify all three models.

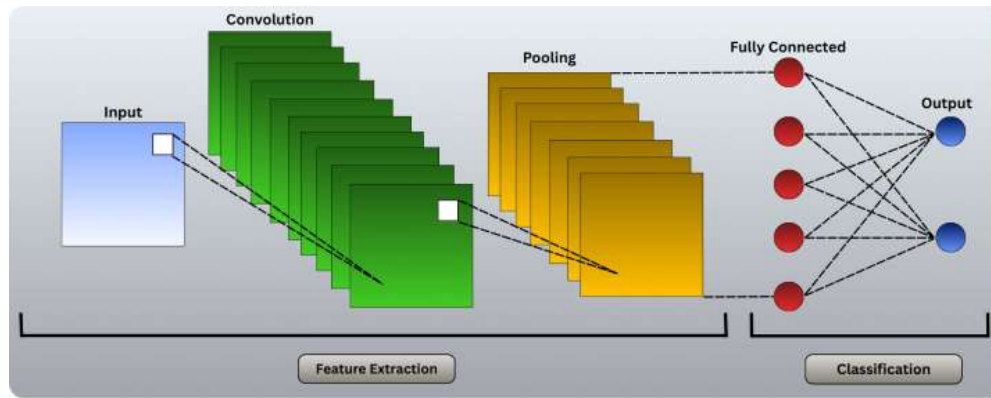


Fig. 4. Architectural diagram of CNN model.

7.6 Optimization Algorithms and Hyperparameters

The proposed CNN pipeline for military aircraft classification utilizes the Adam optimization algorithm for all three models, leveraging adaptive moment estimation for efficient convergence. Parameter updates are computed as

$$\theta_{t+1} = \theta_t - \eta \cdot \frac{\hat{m}_t}{\sqrt{\hat{v}_t + \epsilon'}}$$

where η denotes the learning rate. Hyperparameter tuning is performed using Keras Tuner (Hyperband strategy), exploring convolutional depth $L \in [1, 3]$, filter sizes $f_i \in [32, 256]$, and dense layer units $u \in [128, 1024]$. The learning rate is selected from $\eta \in \{10^{-3}, 10^{-4}\}$, while dropout regularization is varied within $p \in [0.1, 0.5]$ to mitigate overfitting. Batch-wise optimization employs categorical cross-entropy loss

$$L = - \sum_{i=1}^C y_i \log(\hat{y}_i)$$

Early stopping and validation monitoring are used to ensure generalization across high-resolution satellite image datasets.

7.7 Evaluation Metrics

Model performance was evaluated using classification accuracy. Additionally, Precision, recall, and F1-score were computed per class to assess imbalance sensitivity. Overall performance was validated on a hold-out set, ensuring generalization for high-resolution satellite-based military aircraft classification.

1. Accuracy

Accurately characterizing what percentage of prediction outcomes is accurately characterized.

2. Precision

Precision can be calculated by first characterizing the number of objects correctly characterized as true positives divided by the number of true positives plus false positives.

3. Recall

Recall can be calculated by characterizing the number of true positives divided by the number of true positives plus false negatives.

4. F1-Score

The F1 score is the harmonic mean of precision and recall, thus, the F1 score combines precision and recall to create a single measure.

8. RESULTS AND DISCUSSION

8.1 Experimental Results

Table 2. Results Obtained from Custom CNN-1 Model with Different Training and Testing Ratios

Training Testing Ratio	Model Used	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
90:10	Custom	93.35	93.00	93.00	93.00
85:15	CNN_1	93.52	93.00	93.00	93.00

80:20		93.28	93.00	93.00	93.00
75:25		94.01	94.00	94.00	94.00
70:30		92.02	92.00	92.00	92.00
65:35		92.58	92.00	92.00	92.00
60:40		91.90	92.00	92.00	92.00
Average		92.95	92.71	92.71	92.71

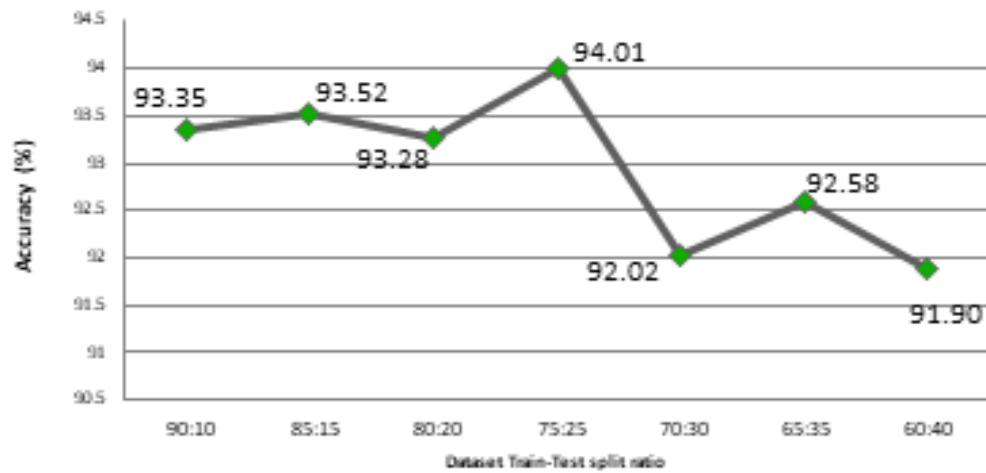


Fig. 5. Graphical representation of Accuracy obtained from Custom CNN-1 model with different dataset Training, and Testing Ratios.

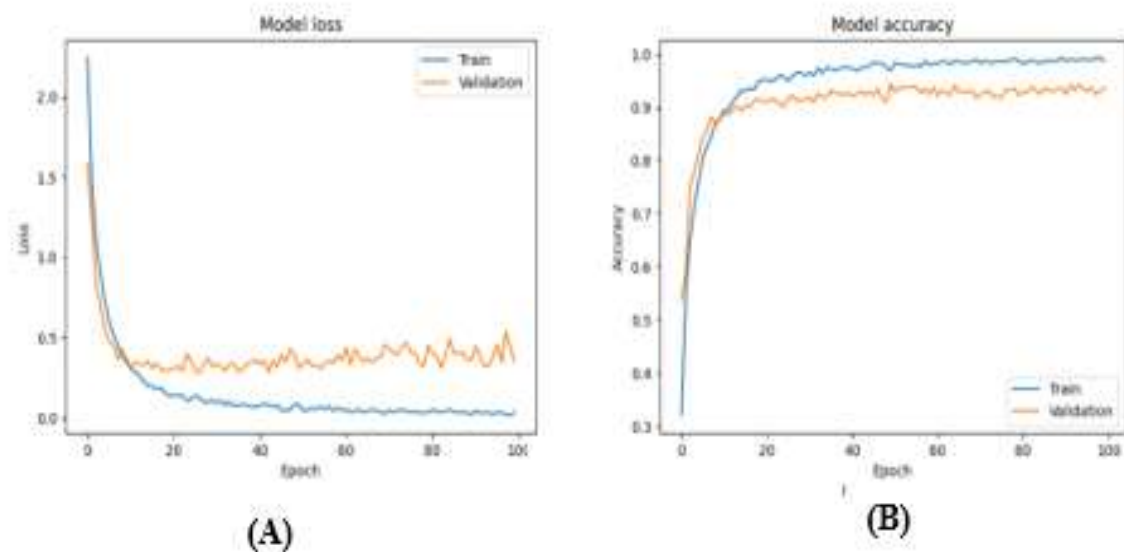


Fig. 6. (A) Training Loss Curve **(B)** Training Accuracy Curve of the Custom CNN-1 model when trained and tested on 85:15 split ratio.

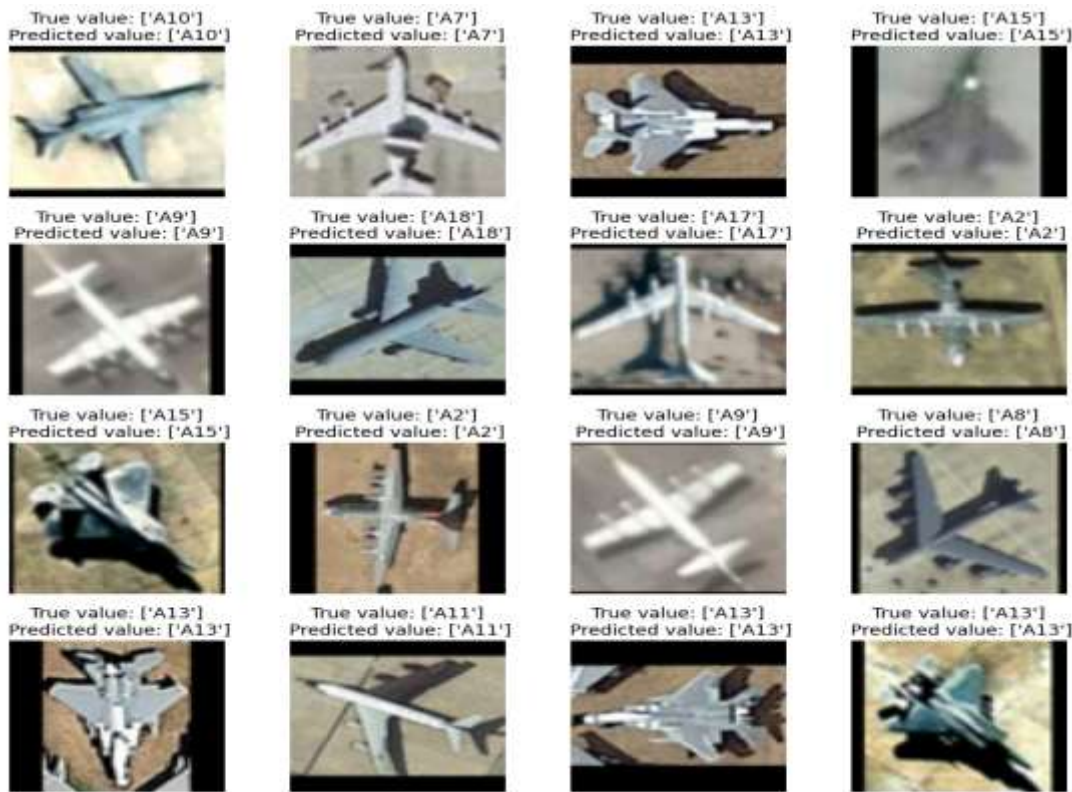


Fig. 7. Output predictions showcasing Predicted Values against True Values when Custom CNN-1 model tested on Test Set.

Table 3. Results Obtained from Custom CNN-2 Model with Different Training and Testing Ratios

Training Testing Ratio	Model Used	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
90:10	Custom CNN_2	93.35	93.00	93.00	93.00
85:15		93.77	94.00	94.00	94.00
80:20		93.41	93.00	93.00	93.00
75:25		93.19	93.00	93.00	93.00
70:30		91.34	92.00	91.00	91.00
65:35		92.65	93.00	93.00	93.00
60:40		91.17	91.00	91.00	91.00
Average		92.69	92.71	92.57	92.57

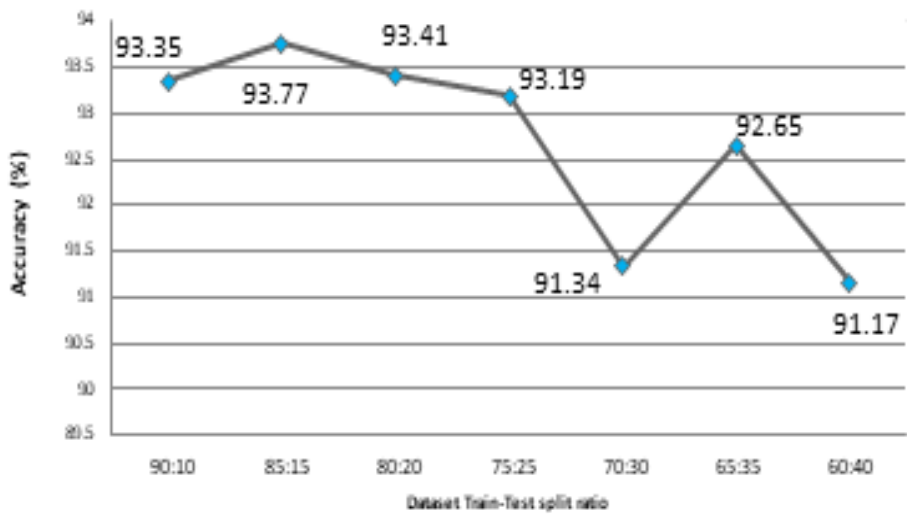


Fig. 8. Graphical representation of Accuracy obtained from CNN-2 model with different dataset Training, and Testing Ratios.

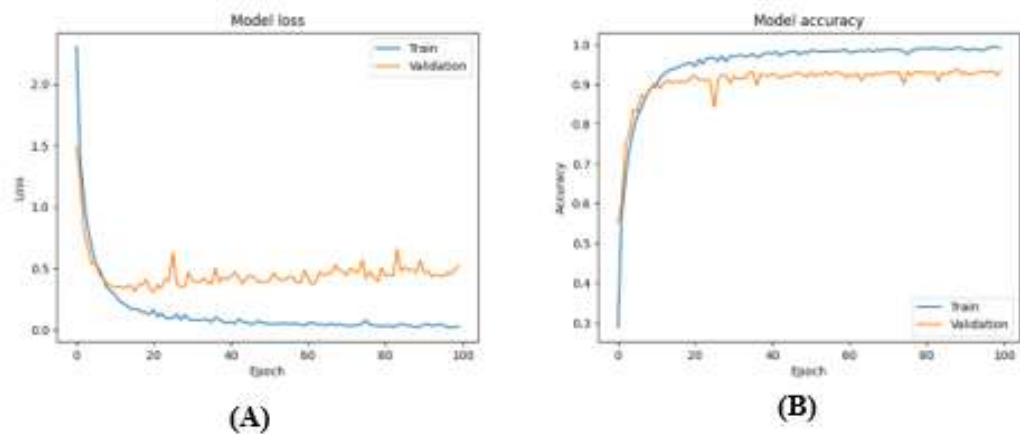


Fig. 9. (A) Training Loss Curve (B) Training Accuracy Curve of the Custom CNN-2 model when trained and tested on 80:20 split ratio.



Fig. 10. Output predictions showcasing Predicted Values against True Values when Custom CNN-2 model tested on Test Set.

Table 4. Results Obtained from Custom CNN-3 Model with Different Training and Testing Ratios					
Training Testing Ratio	Model Used	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
90:10	Custom CNN_3	93.48	94.00	94.00	93.00
85:15		93.60	94.00	94.00	94.00
80:20		94.11	94.00	94.00	94.00
75:25		93.09	93.00	93.00	93.00
70:30		91.13	91.00	91.00	91.00
65:35		92.18	93.00	93.00	92.00
60:40		91.42	92.00	92.00	92.00
Average		92.71	93.00	93.00	92.71

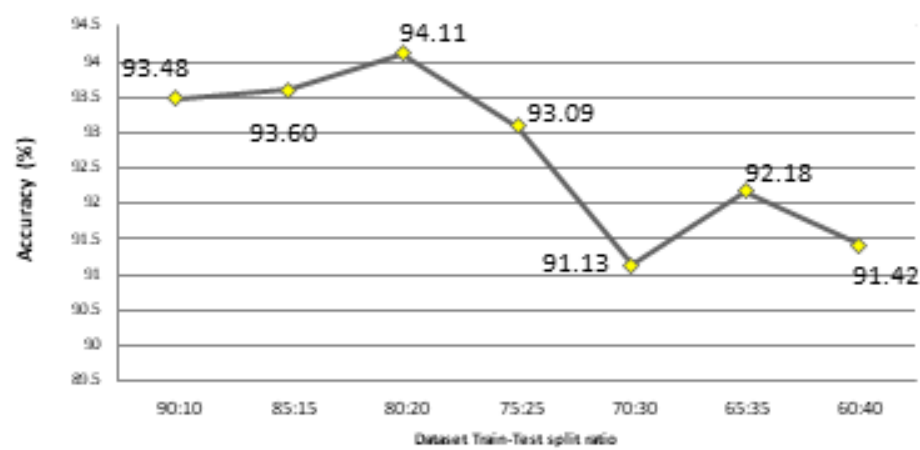


Fig. 11. Graphical representation of Accuracy obtained from CNN-3 model with different dataset Training, and Testing Ratios.

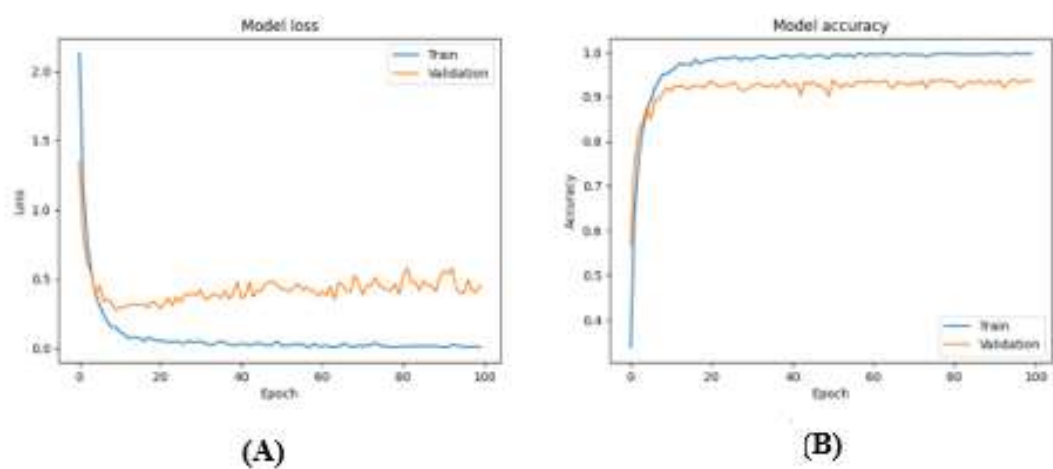


Fig. 12. (A) Training Loss Curve **(B)** Training Accuracy Curve of the Custom CNN-3 model when trained and tested on 85:15 split ratio.

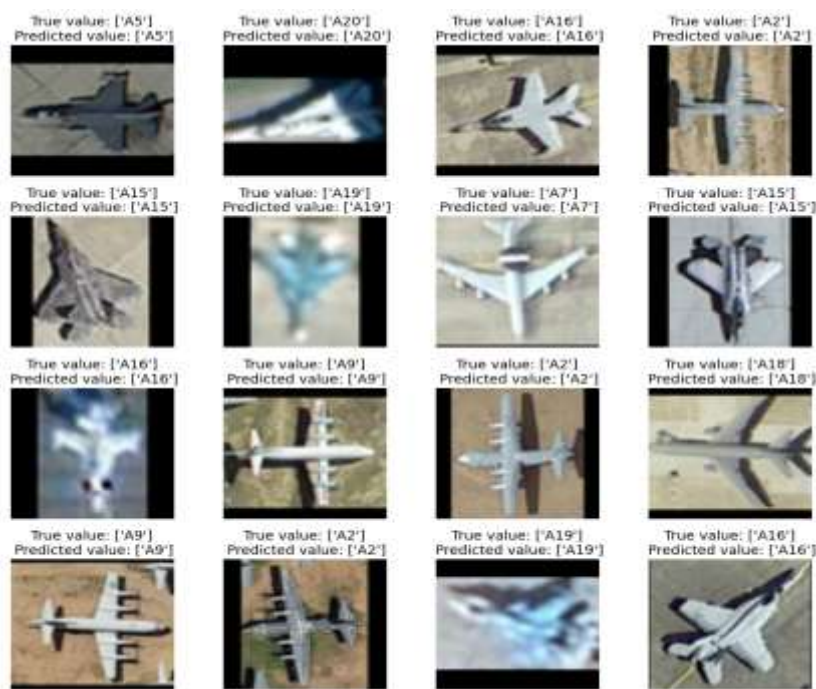


Fig. 13. Output predictions showcasing Predicted Values against True Values when Custom CNN-3 model tested on Test Set.

8.2 Comparative Analysis

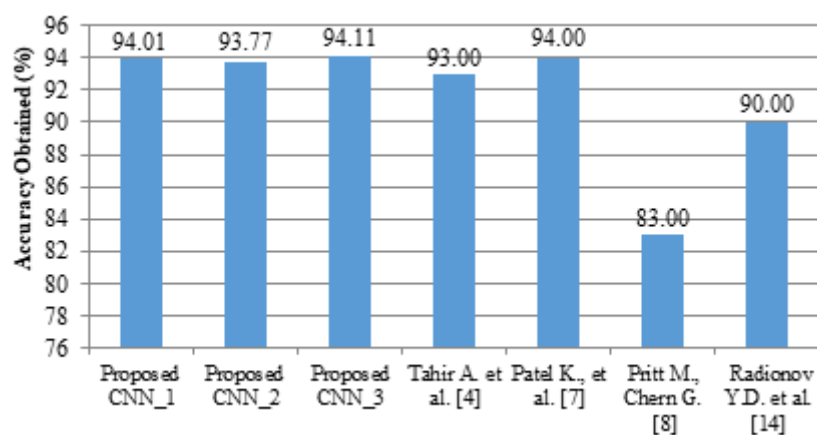


Fig. 14. Comparative analysis of the proposed Custom CNN classification models against existing methodologies.

The performance of the three proposed deep learning-based CNN architectures were evaluated comparatively with an emphasis on consistency and reliability in classifying military aircraft using satellite high resolution images. Custom CNN_1 had the highest average accuracy score at 92.95%, demonstrating superior ability to generalise well across variable training and test ratios. Custom CNN_2 had an average accuracy of 92.69% and demonstrated stable precision and recall performance. Custom CNN_3 achieved the highest individual accuracy score of 94.11% with respect to all three architectures through extensive hyperparameter tuning but only produced an overall average accuracy of 92.71%.

8.3 Limitations

The proposed CNN architecture has limitations in its current design. The CNN training process utilizes resized inputs therefore, many of the fine scale spatial details that would help to differentiate between two visually similar military aircraft are lost. Also, variability in classification performance resulting from different train and test ratio values indicates that the proposed framework is sensitive to both data distribution and class imbalance. Lastly, a lack of extensive data augmentation and transfer learning processes may constrain the ability to generalize performance across many high-resolution satellite image datasets. Similar methodological concerns have been discussed in deep-learning-based medical image classification, particularly regarding annotation quality, data leakage, and the need for external validation. Accordingly, future studies should evaluate the proposed aircraft-classification framework on independent satellite-image datasets to establish its generalizability beyond the dataset used in the present experiments [15].

8.4 Practical Real-Time Implementations

One possible scenario is utilizing a convolutional neural network (CNN) based military aircraft classifier for working with real-time aerial surveillance and defense intelligence applications using high resolution satellite imagery for automated target recognition. By utilizing a lightweight architecture or framework and optimizing the hyperparameters, these types of CNN models have the ability to provide efficient inference and therefore are very well suited for edge assisted geospatial monitoring type platforms. In addition, by integrating into existing remote sensing and GIS pipelines, it will enable rapid situational awareness and decision-making capabilities within defense related reconnaissance environments.

9. CONCLUSION AND FUTURE SCOPE

This study presented deep learning framework to classify military aircraft using very high-resolution satellite imagery using three different custom CNN architectures. The custom CNN_1 architecture achieved the highest average overall accuracy. The custom CNN_3 architecture recorded the highest accuracy across all evaluations. Therefore, convolutional feature extraction and hyperparameter optimization were demonstrated to be effective at differentiating between aircraft categories given different characteristics of the dataset during evaluation. Overall, while the performance of the framework produced positive results, there are still challenges with low-resolution inputs, cropped objects, cropping-related attributes, and variation of datasets.

Future work will include transferring learning models, advanced forms of data augmentation, and expanding the framework for real-time object detection with YOLO-type architectures for an improved capability to deploy the system for military operations.

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