International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 05 | May-2024 SJIF Rating: 8.448 ISSN: 2582-3930

ENHANCED AIRCRAFT DETECTION IN REMOTE SENSING IMAGERY THROUGH DEEP LEARNING ALGORITHM

Satheeshkumar K[1], Arun P[2], Harish K[3] , Karthik P[4], Vidun K[5]

Department of Computer Science and Engineering, University College of Engineering, Thirukkuvalai
(A constituent College of Anna University::Chennai and Approved by AICTE, New Delhi)

---***---

Abstract - Aircraft recognition in computer vision technology is essential, involving extracting the plane's shape via a recognition processor. Image recognition, identifying objects in digital media, is pivotal in various applications, like automating industrial lines and security surveillance. Aircraft, with their diverse characteristics, pose challenges like varying size, texture, and coloration, compounded by disruptions like clutter and contrast differences. Neural networks, particularly convolutional neural networks, are utilized for recognition. The process involves median filtering for image processing, followed by feature extraction, utilizing shape, size, and texture. Superpixel segmentation reduces dimensionality, and convolutional neural networks classify using templates. An alert system notifies administrators upon aircraft detection, aiming for higher accuracy than current algorithms.

Key Words: Image Processing, Superpixel Segmentation, Alert system, Convolutional Neural Network, Feature Extraction.

1.INTRODUCTION

Modern remote sensing technology has significantly enhanced the information extracted from satellite photos, proving invaluable for military operations. Analysis of military data, strategic planning, and airport surveillance now heavily rely on remote sensing object detection, particularly for identifying airplanes. However, challenges such as small target sizes, susceptibility to lighting and weather conditions, and crowded aircraft configurations pose obstacles to background separation in remote sensing imagery.

In the past, machine learning techniques handled target identification. Yet, with the rise of deep learning, especially in computer vision, there's been a paradigm shift in object detection and image classification. Traditional machine learning and deep learning methods are now employed in remote sensing, with convolutional neural networks (CNNs) showing promise in overcoming detection challenges.

CNNs excel in feature extraction and hierarchical representation learning, adapting well to remote sensing tasks by automatically learning relevant features from raw data. Techniques like data augmentation, transfer learning, and ensemble methods further bolster CNN-based models in remote sensing applications. Pre-trained CNN models like VGG, ResNet, or EfficientNet serve as feature extractors, initially trained on large-scale datasets and fine-tuned on remote sensing data for specific tasks like airplane detection.

Moreover, methods such as Region-based CNN (R-CNN), including Faster R-CNN and Mask R-CNN, enable precise object localization and segmentation in remote sensing images. These techniques partition images into regions of interest, applying CNNs to each region for accurate object detection and classification, including airplanes.

Besides CNNs, other deep learning architectures like recurrent neural networks (RNNs) and attention mechanisms are explored for remote sensing tasks, providing alternative approaches for temporal data handling and spatial dependency capture.

Overall, deep learning has transformed remote sensing object detection by offering robust solutions to challenges such as small target sizes, varying environmental conditions, and complex background interference. As technology progresses, further innovations in deep learning are poised to enhance the capabilities of remote sensing systems for both military and civilian applications..

2.LITERATURE SURVEY

TITLE: COMPARATIVE RESEARCH ON DEEP LEARNING APPROACHES FOR AIRPLANE DETECTION FROM VERY HIGH-RESOLUTION SATELLITE IMAGES

AUTHOR: UGUR ALGANCI

Object detection from satellite imagery has considerable importance in areas, such as defense and military applications, urban studies, airport surveillance, vessel traffic monitoring, and transportation infrastructure determination. Remote sensing images obtained from satellite sensors are much complex than computer vision images since these images are obtained from high altitudes, including interference from the atmosphere, viewpoint variation, background clutter, and illumination differences. Several studies have been conducted on the automatic identification of different targets, such as buildings, aircraft, ships, etc., to reduce human-induced errors and save time and effort. However, the complexity of the background; differences in data acquisition geometry, topography, and illumination conditions; and the diversity of objects make automatic detection challenging for satellite images. Object detection can be thought of as combining two main tasks: the first is object classification, in which the objective is to give a label or category to every object that is detected; the second is object location determination, which includes tasks like segmentation or bounding box regression, to determine the exact location of each object within the images.

Studies conducted so far have focused on improving these two tasks separately or together. In summary, the location of objects on the image is generally determined by scanning the entire image with a sliding window approach and a classifier, which may be selected from the abovementioned methods, which does the recognition task. The classifiers trained with these methods have a low size of parameters. Therefore, scanning the entire image with small strides allows an acceptable pace at object detection.

TITLE: AIRCRAFT DETECTION FOR REMOTE SENSING IMAGES BASED ON DEEP CONVOLUTIONAL NEURAL NETWORKS

AUTHOR: LIMING ZHOU

In this paper, we propose the MSDN network structure, which imports the multiscale detection model, by adding a smaller detection scale to the backbone of Darknet-53 to detect the aircrafts in small size. The DAWM module of InceptionResNet proposes a technique to reduce background noise by incorporating convolutions of different sizes into the network. This method improves the network's capacity to generalize by expanding its perceptual field and strengthening its nonlinear functions. Furthermore, the DAWM module is included into the MSDN network, creating a novel structure called MSRDN that is intended to address issues like background noise and small-scale objects. A multiscale detection model is incorporated into the MSDN network to address the problem of missed tiny planes. Grid cells are divided by adding a lower detection scale to the Darknet-53 backbone, which increases the possibility of finding small aircraft inside these cells. Additionally, the Inception-ResNet-inspired DAWM module is used to counteract background noise. By adding different sized convolutions, the DAWM module broadens the perceptual area of the network and improves its generalization performance, making it able to withstand background noise and adjust to different settings. The integration of the DAWM module into the MSDN network structure, known as MSRDN, addresses both of the aforementioned difficulties in one go. To maximize outcomes, the DAWM module is positioned strategically throughout the MSDN network. Thereby, we get the MSRDN-F, MSRDN-M, and MSRDN-B.

TITLE: TRANSEFFIDET: AIRCRAFT DETECTION AND CLASSIFICATION IN AERIAL IMAGES BASED ON EFFICIENTDET AND TRANSFORMER

AUTHOR: YANFENG WANG

Analysis and optimization algorithm based on image data is a hot issue in recent years. Image processing is widely used in military settings in addition to civil applications. In the military domain, aircraft objects in military sites and airports are detected during wartime using aerial and remote sensing photography. Its capacity to quickly and precisely estimate the number of enemy aircraft and their movements is crucial for information gathering and strategic deployment. It helps commanders make well-informed tactical decisions and greatly increases the likelihood of victory in combat. As a result, military research places a high priority on aircraft detection in photography. Differentiating between military and civilian aircraft is also essential, as it may reduce the number of civilian casualties in conflict areas. Reliable airplane recognition and categorization in aerial images is necessary for automating site analysis, especially for producing alerts for anomalous events. Achieving this accuracy is of high research value. Traditional object detection methods involve manual feature extraction and designing classifiers tailored to specific detection tasks. However, these methods struggle to extract robust features and are highly susceptible to environmental noise, limiting their practical utility. Despite advancements, aircraft detection in aerial imagery still confronts numerous challenges, including poor image quality due to adverse environmental conditions, similar shapes among different aircraft types, and the expansive sky background. Overcoming these challenges necessitates the development of robust technologies and systems capable of reliably detecting and classifying aircraft based on their distinctive characteristics. Artificial intelligence (AI) and Deep Learning (DL) hold promise in addressing these requirements effectively.

TITLE: IMPROVED MASK R-CNN FOR AIRCRAFT DETECTION IN REMOTE SENSING IMAGES

AUTHOR: QIFAN WU

Many remote sensing aircraft detection methods based on neural networks have been proposed because of their strong feature abstraction ability and high accuracy. Neural network algorithms eliminate the need for human feature engineering and data annotations by encapsulating all four steps of classic object detection algorithms into a single, cohesive framework. Neural network models for object detection and segmentation can be divided into two categories: single-stage models and two-stage models. This division is made according to how the models generate candidate regions. Two-stage models provide better detection accuracy, whereas single-stage versions dominate in quick detection times. A noteworthy development is Mask R-CNN, which can combine object detection and instance segmentation in a seamless manner into an end-to-end deep learning architecture without the need for extra data annotations. Interestingly, it uses ROI Align rather than ROI Pooling. The fundamental framework for this work is Mask R-CNN, a traditional multi-task two-stage neural network. We offer an improved Mask R-CNN model designed for aircraft recognition and segmentation in remote sensing photos, acknowledging the strategic importance and usefulness of airplanes as both necessary resources and modes of transportation, especially in the field of remote sensing photography. We use the WFA-1400 remote sensing aircraft mask dataset to improve aircraft target detection performance. We also incorporate dilated convolutions and modified SC-conv into the underlying Mask R-CNN model to enrich high-level feature information.

3. SYSTEM OVERVIEW

One essential component of artificial intelligence (AI) is machine learning, which enables computers to learn and improve on their own without explicit programming through experience. At the heart of machine learning is the development of computer programs that can use data to learn for themselves. This educational process begins with the intake of observations or data, which can be examples, firsthand experiences, or instructional inputs. The objective is to identify trends and improve the ability to make decisions for tasks in the future. The main goal is to provide computers the ability to learn and adapt on their own without assistance from humans, which will promote efficiency and continuous progress.

3.1 MACHINE LEARNING METHODS

Machine learning algorithms are typically classified as supervised or unsupervised. In supervised learning, data scientists provide both input and desired output, along with feedback on prediction accuracy during training. They select relevant features for the model to analyze, and once trained, it applies learned patterns to new data. On the other hand, unsupervised algorithms, like neural networks, don't require labeled data. They employ deep learning techniques to iteratively process data and draw conclusions. Unsupervised learning is employed for complex tasks such as image recognition and natural language generation, relying on vast amounts of training data to identify intricate correlations between variables. These algorithms leverage big data to learn associations and interpret new data effectively.

- **Supervised machine learning algorithms** leverage labeled examples from past data to predict future events by extrapolating what has been learned. Through an initial analysis of a predefined training dataset, these algorithms derive an inferred function, facilitating predictions about output values. Following adequate training, the system becomes proficient in generating targets for novel inputs. By comparing its output with the correct intended output, the learning algorithm identifies errors and iteratively refines the model to enhance accuracy.

- In contrast, **unsupervised machinelearning algorithms** are used when the information used to train is neither classified nor labeled. The study of unsupervised learning explores how systems use input without explicit labels to identify patterns and deduce underlying structures.The system doesn't figure out the right output, but it explores the data and can draw inferences from datasets to describe hidden structures from unlabeled data.

- **Semi-supervised machine learning algorithms** fall somewhere in between supervised and unsupervised learning, since they use both labeled and unlabeled data for training – typically a small amount of labeled data and a large amount of unlabeled data. The systems that use this method are able to considerably improve learning accuracy. Usually, semi-supervised learning is chosen when the acquired labeled data requires skilled and relevant resources in order to train it / learn from it. Otherwise, acquiringunlabeled data generally doesn't require additional resources.

- **Reinforcement machine learning algorithms** An agent that interacts with its environment through activity and feedback in the form of rewards or penalties is said to be using reinforcement learning techniques. Two essential components of reinforcement learning are the idea of delayed rewards and trial-and-error exploration. By use of this procedure, devices and software agents are capable of self-adjusting their actions to optimize their performance in a specific setting. The continuous feedback loop, in which the agent learns from basic reward signals to identify the most effective actions, is the core of reinforcement learning.

- Machine learning enables analysis of massive quantities of data. While it generally delivers faster, more accurate results in order to identify profitable opportunities or dangerous risks, it may also require additional time and resources to train it properly. Combining machine learning with AI and cognitive technologies can make it even more effective in processing large volumes of information.

3.2 IMAGE PROCESSING

Image processing involves applying mathematical operations to images, treating them as signals. It can encompass various inputs, including images, series of images, or videos, producing either modified images or extracted characteristics. Digital image processing is predominant, but optical and analog methods are also feasible. Image acquisition is termed imaging. Computer graphics generates images from models, while computer vision deciphers image content. Image analysis extracts information, vital in fields like genetics or finance. Although computers excel in data analysis, human perception remains crucial in tasks requiring higher-level interpretation. Image editing involves modifying digital or traditional images using tools like airbrushes or software programs. Raster images, composed of pixels, are edited through algorithms, enabling various enhancements. Graphics software merges images, with techniques like silhouetting to isolate objects from backgrounds. Alpha compositing allows soft transitions between images. Composite images often utilize transparent layers, preserving pixel data for future edits.

3.3 SEGMENTATION

Image segmentation in computer vision involves dividing a digital image into multiple segments or sets of pixels, aiming to simplify or alter its representation for easier analysis. This process is crucial for locating objects and boundaries within images. Each pixel is assigned a label based on shared characteristics, such as color or intensity, resulting in segments covering the entire image or contours outlining objects. In medical imaging, segmentation aids in creating 3D reconstructions from image stacks using interpolation algorithms like marching cubes. Segmenting an image partitions it into meaningful parts, facilitating further processing. This division may rely on features like color or texture. Segmentation precedes denoising to restore the original image and aims to streamline information for analysis. It's integral in tasks like image analysis and compression, contributing to efficient data handling and interpretation.

SYSTEM ARCHITECTURE

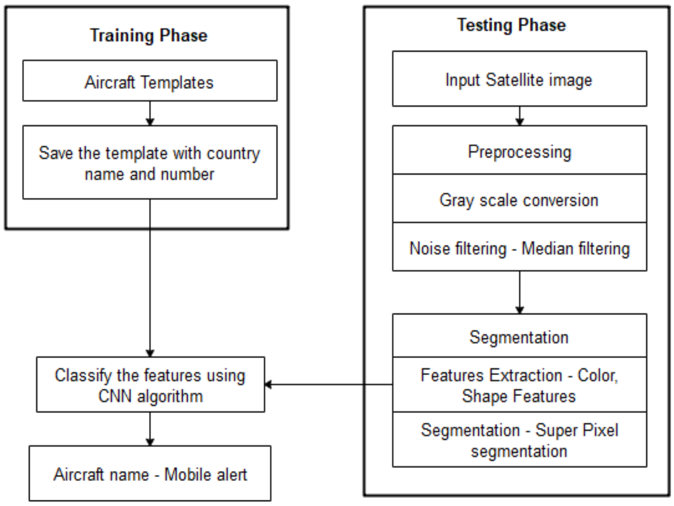


Fig.1 system architecture

4. ALGORITHM

4.1 SUPERPIXEL SEGMENTATION

Image pixels are the base unit in most image processing tasks. Superpixels are not natural objects; rather, they are the result of discrete picture representation. They are the end consequence of oversampling an image, or more specifically, of perceptually grouping pixels. Nevertheless, there are disadvantages to using superpixel segmentation as a preprocessing step, such as higher CPU requirements for superpixel computation and the possible loss of important image edges included within superpixels. Furthermore, dealing with the non-grid superpixel arrangement may present difficulties for further processing steps, highlighting the significance of carefully choosing the superpixel algorithm and its parameters based on the particular application requirements.

A major insight from our previous work on extensive comparison of superpixel segmentation algorithms is the existence of several trade-offs for such algorithms. The most intuitive is the trade-off between segmentation quality and runtime. However, there exist many more between these two and a multitude of other performance measures. We designed two new superpixel segmentation algorithms, based on existing algorithms, that provide better balanced trade-offs.

4.2 CONVOLUTIONAL NEURAL NETWORK (CNN)

A Convolutional Neural Network (CNN) is adept at extracting topological properties from input images by leveraging local receptive fields, shared weights, and spatial or temporal sub-sampling. CNNs are resilient to distortions and basic geometric transformations such as translation, scaling, rotation, and squeezing. By organizing convolutional layers into planes of neurons called feature maps, CNNs can detect specific features within an image. These layers employ convolution kernels to extract features from local receptive fields, allowing neurons to share connection structures and weights for efficiency. This process resembles convolving the input image with a small kernel, facilitating the extraction of

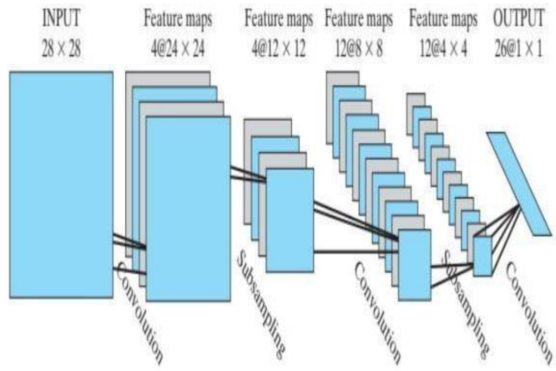


Fig.2 CNN Frame work

elementary visual features like edges. In our proposed CNN structure, multiple features can be extracted from each original eye data, with each feature having n^3 dimensions. The network is trained using backpropagation, similar to standard neural networks, to optimize the classification of the extracted features.

5. IMPLEMENTATION

5.1 MODULE LIST

- AIRCRAFT IMAGE ACQUISITION
- PREPROCESSING
- SEGMENTATION
- AIRCRAFT CLASSIFICATION
- ALERT SYSTEM

5.2 MODULES DESCRIPTION

AIRCRAFT IMAGE ACQUISITION

Image recognition identifies items or elements in digital images or videos, crucial for applications like production line automation, toll booth monitoring, and security surveillance. Algorithms include optical character recognition, face recognition, license plate matching, and scene change detection. The process typically involves image processing techniques such as noise removal, followed by low-level feature extraction to detect lines, regions, and specific surfaces. This module handles satellite images captured by sensors, accommodating images of any type and size, potentially recognizing partial or full shapes of aircraft.

PREPROCESSING

In various fields like photography and computing, grayscale images represent pixel values as intensity levels, unlike binary images which only have black and white pixels. Grayscale images contain shades of gray, resulting from measuring light intensity at each pixel. These images can be monochromatic, capturing a narrow band of frequencies across the electromagnetic spectrum. In this module, RGB images are converted to grayscale before applying filtering techniques to enhance image properties, facilitating processing in subsequent modules.

SEGMENTATION

Super-pixel segmentation finds wide application in computer vision tasks like semantic segmentation, visual tracking, and image classification. In this module, aircraft features such as color, shape, and texture are extracted and analyzed within satellite imagery to identify aircraft regions accurately. Despite the growing popularity of super pixels, few algorithms efficiently produce regular, compact super pixels with low computational overhead. Our solution, SLIC (Simple Linear Iterative Clustering), addresses this challenge by clustering pixels in a combined five-dimensional color and image plane space, yielding compact, nearly uniform super pixels, enhancing segmentation precision and efficiency.

AIRCRAFT CLASSIFICATION

The detection of aircraft in satellite images employs a neural network algorithm, utilizing template matching in digital image processing. A sliding window traverses image sequences to identify potential matches with a reference target. Regional feature matching evaluates similarity between the target model and window pixels. Segmentation module labels components for extracting region features, describing characteristics. Correlation coefficient measures object similarity for detection and tracking. Extracted features are matched with a database using templates, implementing a Classifier to scrutinize image pixel regions. Neural network matching aids in aircraft type recognition within this module.

ALERT SYSTEM

In this module, send alert to the admin by SMS communication. After successful classification of aircraft pixels to predict aircraft based on templates.

6. SOFTWARE DESCRIPTION

6.1 PYTHON

Python, a high-level, interpreted programming language, boasts wide application across domains like web development, scientific computing, data analysis, AI, and machine learning. Originally released in 1991 by Guido van Rossum, Python's popularity stems from its simplicity, readability, and adaptability. Its user-friendly syntax caters to programmers of all levels, supported by an extensive standard library offering modules for various tasks. Python's vibrant community continuously enriches it with open-source libraries and packages, enhancing its capabilities. As an interpreted language, Python's line-by-line execution enables rapid development, testing, debugging, and maintenance. Its versatility shines in web development with frameworks like Django and Flask, scientific computing with NumPy and Pandas, and machine learning with TensorFlow and PyTorch. Additionally, Python's ease of use makes it ideal for scripting and automation. Overall, Python stands as a potent tool, celebrated for its accessibility, effectiveness, and community support.

Python has a wide range of applications, including:

Data Science: Python is one of the most popular languages for data science, thanks to libraries like NumPy, Pandas, and Matplotlib that make it easy to manipulate and visualize data.

Machine Learning: Python is also widely used in machine learning and artificial intelligence, with libraries like TensorFlow, Keras, and Scikit-learn that provide powerful tools for building and training machine learning models.

Web Development: Python is commonly used in web development, with frameworks like Django and Flask that make it easy to build web applications and APIs.

Scientific Computing: Python is used extensively in scientific computing, with libraries like SciPy and SymPy that provide powerful tools for numerical analysis and symbolic mathematics.

In addition to its versatility and ease of use, Python is also known for its portability and compatibility. Python code can be run on a wide range of platforms, including Windows, macOS, and Linux, and it can be integrated with other languages like C and Java.

Overall, Python is a powerful and versatile programming language that is well-suited for a wide range of applications, from data science and machine learning to web development and scientific computing. Its simplicity, readability, and large community of developers make it an ideal choice for beginners and experts alike.

There are two attributes that make development time in Python faster than in other programming languages:

1.Python is an interpreted language, which precludes the need to compile code before executing a program because Python does the compilation in the background. Because Python is a high-level programming language, it abstracts many sophisticated details from the programming code. Python focuses so much on this abstraction that its code can be understood by most novice programmers.

2.Python code tends to be shorter than comparable codes. Although Python offers fast development times, it lags slightly in terms of execution time. Compared to fully compiling languages like C and C++, Python programs execute slower. Of course, with the processing speeds of computers these days, the speed differences are usually only observed in benchmarking tests, not in real-world operations. In most cases, Python is already included in Linux distributions and Mac OS X machines.

One of the strengths of Python is its rich ecosystem of third-party libraries and tools. These libraries provide a wide range of functionality, from scientific computing and data analysis to web development and machine learning. Some popular Python libraries and frameworks include:

NumPy: a library for numerical computing in Python, providing support for large, multi-dimensional arrays and matrices, along with a large collection of mathematical functions to operate on these arrays.

Pandas: a library for data manipulation and analysis in Python, providing support for reading and writing data in a variety of formats, as well as powerful tools for manipulating and analyzing data.

Matplotlib: a plotting library for Python that provides a variety of visualization tools, including line plots, scatter plots, bar plots, and more.

TensorFlow: an open-source machine learning library for Python that provides a variety of tools and algorithms for building and training machine learning models.

Django: a popular web framework for Python that provides a full-stack framework for building web applications, with support for everything from URL routing to user authentication and database integration.

Python's popularity has also led to a large and active community of developers who contribute to open-source projects and share code and resources online. This community provides a wealth of resources for learning Python, including tutorials, online courses, and forums for asking and answering questions.

6.2 TENSORFLOW LIBARIES IN PYTHON

TensorFlow, an open-source machine learning framework by Google Brain Team, is renowned for its prowess in constructing and training machine learning models, particularly deep neural networks. Its strength lies in handling vast datasets and intricate computations, ideal for deep neural network training. TensorFlow facilitates parallel computations across CPUs or GPUs, expediting training processes. With its Keras API, developers can effortlessly construct and train models. Additionally, TensorFlow offers diverse tools and libraries for seamless integration with other Python frameworks, alongside built-in support for data preprocessing and visualization, streamlining data preparation and model analysis. Notably, TensorFlow excels in model deployment across various platforms, including mobile devices and the web, showcasing its versatility and adaptability in real-world applications.

6.3 PYCHARM

PyCharm, an IDE for Python by JetBrains, offers a suite of features including code completion, debugging, analysis, refactoring, and version control integration. It comes in two editions: Community (CE) for basic Python development, and Professional (PE) with advanced capabilities like remote development and web tools. Available on Windows, macOS, and Linux, PyCharm supports Python versions from 2.7 to 3.10, catering to a wide user base across different operating systems and Python versions.

Features:

- Intelligent code completion
- Syntax highlighting
- Code inspection
- Code navigation and search
- Debugging
- Testing
- Version control integration
- Web development support
- Scientific tools support
- Database tools support

7. RESULT

The system undergoes training and testing phases. The administrator collects a large dataset to label aircraft images and trains the dataset to store them. Then, the administrator utilizes the testing option to upload aircraft images, which can be either full or partial images. Subsequently, the system analyzes the uploaded image and initiates the segmentation process, employing superpixel segmentation to extract aircraft features such as color, shape, and texture. It displays a yellow outline around the uploaded aircraft to predict its identity.

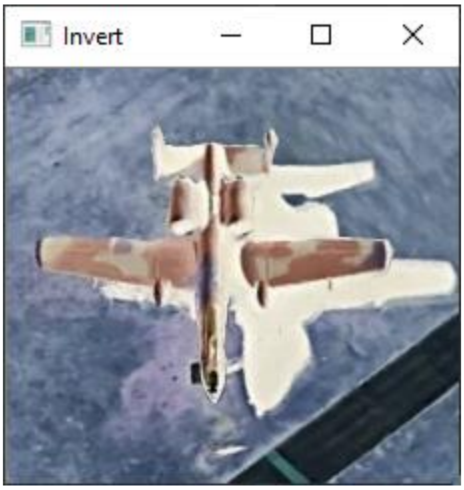


Fig.3

When converting an RGB image to grayscale, we need to consider the RGB values for each pixel and produce a single value as output, representing the brightness of that pixel.

TRAINING ACCURACY

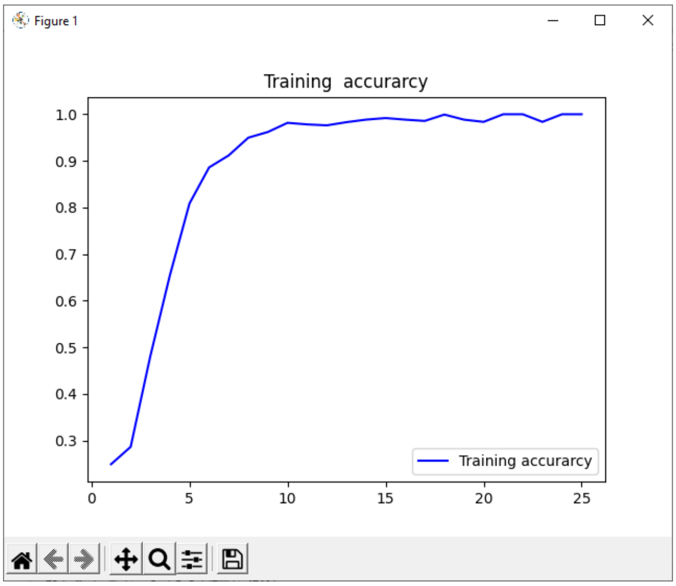


Fig.4

TRAINING LOSS

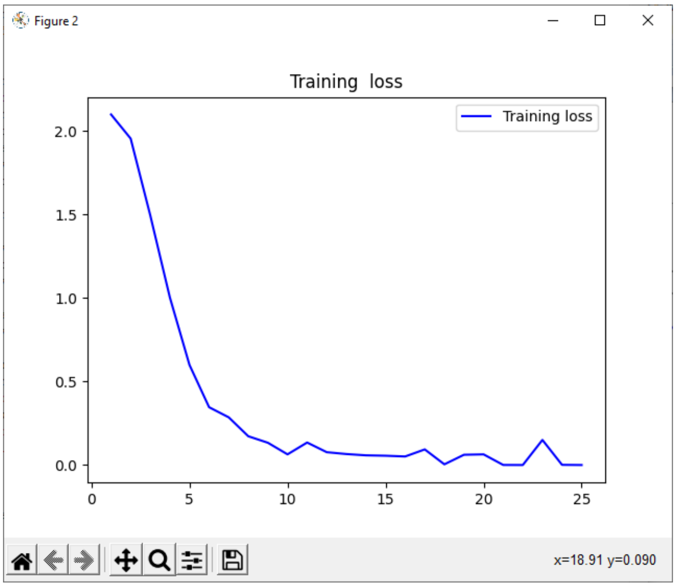


Fig.5

Fig.6

Volume: 08 Issue: 05 | May-2024 SJIF Rating: 8.448 ISSN: 2582-3930

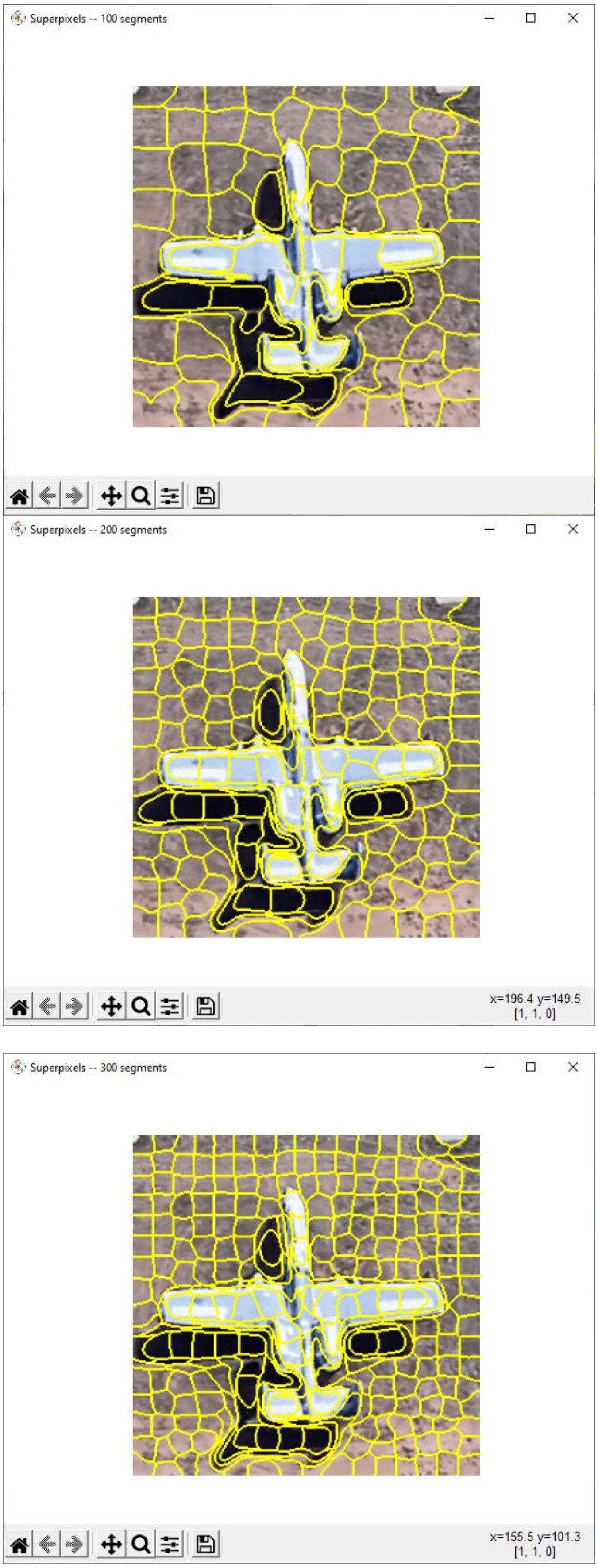
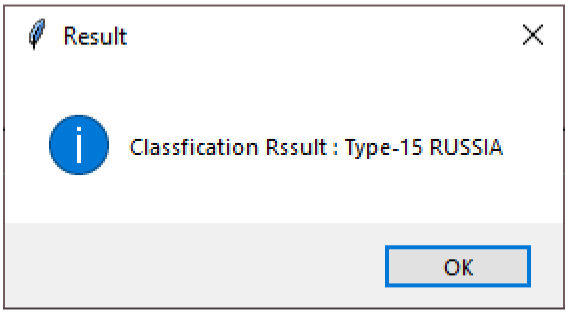


Fig.7

Result:



8.CONCLUSION

The project introduced an aircraft recognition system for satellite image surveillance, employing super pixel segmentation and template matching for improved accuracy and low computational complexity in tracking. Neural network analysis enhanced segmentation and tracking of target objects, demonstrating better efficiency through simulation. A new automatic target classifier was proposed, utilizing a combined neural networks' system via ISAR image processing. This introduced novel automatic classification procedures and improved multimedia processing for object detection. A neural classifier, comprising backpropagation artificial neural networks, recognized aircraft targets from ISAR images. The combination of recent image processing techniques enhanced shape and feature extraction, with super pixel descriptors used as input features. Performance analysis compared the proposed approach with conventional multimedia processing and automatic target recognition systems, showing its efficiency in automatic aircraft target recognition through extensive simulation trials.

Future work aims to enhance the performance of individual neural networks by applying optimization algorithms to their learning processes. Additionally, the proposed shape primitives are deemed powerful for aircraft recognition in satellite images. The identification of potential moving objects in time series images through frame-based object tracking is another focus. Future endeavors will concentrate on analyzing different kernel functions' performance across various applications. This comprehensive approach seeks to advance both the accuracy and computational efficiency of aircraft recognition in satellite remote sensing images.

REFERENCE

[1] Alganci, Ugur, Mehmet Soydas, and Elif Sertel. "Comparative research on deep learning approaches for airplane detection from very high-resolution satellite images." Remote sensing 12.3 (2020): 458.

[2] Zhou, Liming, et al. "Detection of Aircraft in Remote Sensing Imagery Utilizing Deep Convolutional Neural

Networks." Electrical and Computer Engineering Journal2021 (2021): 1-16.

[3] Wang, Yanfeng, et al. "TransEffiDet: Detection and Categorization of Aircraft in Aerial Imagery via EfficientDet and Transformer Models." Science and Computational Intelligence.2022 (2022).

[4] Wu, Qifan, et al. "Enhanced Mask R-CNN for Aircraft Detection in Remote Sensing Imagery."Sensors 21.8 (2021): 2618.

[5] Chen, Lifu, et al. "Geospatial transformer is what you need for aircraft detection in SAR Imagery." IEEE Transactions on Geoscience and Remote Sensing 60 (2022): 1-15.

[6] Ucar, Ferhat, Besir Dandil, and Fikret Ata. "Aircraft Detection Framework Utilizing Convolutional Neural Networks in Regional Contexts." International Journal of Engineering Applications and Intelligent Systems.8.3 (2020): 147-153.

[7] Wu, Zhi-Ze, et al. "Weakly Supervised Learning Approach Utilizing Convolutional Neural Networks for Aircraft Detection in Remote Sensing Imagery." IEEE Access 8 (2020): 158097-158106.

[8] Zhang, Peng, et al. "Sfre-net: Scattering feature relation enhancement network for aircraft detection in sar images." Remote Sensing 14.9 (2022): 2076.

[9] Ghosh, Sourish, et al. "AirTrack: Onboard Deep Learning Framework for Long-Range Aircraft Detection and Tracking." arXiv preprint arXiv:2209.12849 (2022).