



e-ISSN: 2319-8753 | p-ISSN: 2347-6710

IJIRSET

International Journal of Innovative Research in
SCIENCE | ENGINEERING | TECHNOLOGY

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 12, Issue 6, June 2023

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 8.423

 9940 572 462

 6381 907 438

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Deep Learning for Aircraft Recognition using CNN

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ABSTRACT: The paper aims to automate the classification of aircraft types using visual images, benefiting aviation, air traffic control, maintenance, research, and security. To overcome the drawbacks of manual identification, a Convolutional Neural Network (CNN) model based on the VGG19 architecture is trained. The paper's main objective is to develop a reliable and accurate aircraft classification system. The CNN model leverages Deep Learning and Computer Vision techniques to efficiently identify aircraft types from input images. The VGG19 architecture, with its convolutional, pooling, and fully connected layers, captures complex patterns in images. The model is trained on a labelled dataset of aircraft images, enabling it to recognize distinctive features of each aircraft type. By using this trained model, problems associated with manual identification are effectively addressed. The model provides an objective and standardized approach, eliminating subjectivity and inconsistency. It reduces the time and resources required for manual identification, offering a faster and more efficient alternative. Moreover, the model is adaptable to various aircraft types and can accommodate new classes, making it suitable for dynamic aviation environments.

KEYWORDS: Aircraft Classification, CNN, VGG19 Architecture, Deep Learning, Computer Vision

I. INTRODUCTION

In the real time aircraft classification, a cutting-edge CNN model employing the VGG19 architecture has been trained to accurately identify the type of aircraft from an input image. VGG19 is a convolutional neural network architecture that consists of 19 layers, primarily utilizing 3x3 convolutional filters and max pooling layers for feature extraction, resulting in deep and accurate image classification. This model has undergone training using a diverse dataset comprising 12 distinct aircraft types. By leveraging the power of deep learning and the intricate layers of VGG19, the model has acquired the ability to discern the unique visual features that distinguish each aircraft category. With its proficiency in aircraft classification, this trained CNN model showcases the potential for advancements in automated aircraft identification and holds promise for various industries, including aviation and defense.

1.1 Problem Definition

The recognition and classification of images through methods such as human experts, drone-based recognition, and manual database searches often require substantial financial investments, specialized expertise, and can be impractical in terms of time, resources, and scalability. In contrast, the proposed system aims to address these limitations by developing and deploying a CNN model with the VGG19 architecture. This model will automatically classify the type of aircraft based on input images, leveraging its training on a diverse dataset of different aircraft type. By training the CNN model to provide accurate outputs, it will serve as an efficient solution for aircraft recognition.

1.2 Existing System

Existing systems for aircraft recognition based on input images include employing human experts with specialized knowledge, developing expensive dedicated hardware systems, utilizing drone-based recognition with costly equipment and complex algorithms, manual database searches that are time-consuming and impractical for real-time scenarios, and custom image analysis software requiring significant financial investment, expertise, and resources.

1.3 Proposed System

A CNN model is trained with the VGG19 architecture to accurately classify various types of aircraft based on input images. The model utilizes a dataset containing 12 distinct aircraft types for training. To facilitate user interaction, a user interface is developed using the Flask framework and connected to the trained model. This user interface or website allows users to upload images and receive predictions on the corresponding aircraft type.

The steps followed in the proposed work are given as

- A. Data Collection
- B. Pre-Processing
- C. Classification model
- D. Recognition
- E. Result

1.4 Requirements Specification Software Requirements

- Operating System: Windows/ Linux
- Technologies: Python 3, OpenCV, Flask Framework
- Tools: Anaconda Navigator, Tensor Flow, Keras, Jupyter Notebook, MySQL, SQLyog

Hardware Requirements

- RAM: 8GB or more
- Memory: 64GB or more
- Processor: Intel/AMD Ryzen processor, NVIDIA GTX/RTX GPU

II. RELATED WORK

Ting Wang, Xiaodong Zeng, Changqing Cao, Wei Li, Zhejun Feng, Jin Wu, Xu Yan, Zengyan Wu, "CGC-NET: Aircraft Detection in Remote Sensing Images Based on Lightweight Convolutional Neural Network", in *IEEE,2022*. End-to-end lightweight aircraft detection framework called CGC-NET (a network based on circle grayscale characteristics), which can accurately detect aircraft with a few training samples. There are only a small number of trainable parameters in CGC-NET, which greatly reduces the need for large datasets. Extensive evaluations indicate the excellent performance of CGC-NET, can be used to accurately detect aircraft targets simply and effectively.

Harika Bandarupally, Harshitha Reddy Talusani, Dr. T Sridevi, "Detection of Military Targets from Satellite Images using Deep Convolutional Neural Networks", in *IEEE,2020*. The presented deep learning model tends to inherently learn an end-to-end mapping between images of lower resolution and higher resolution. This level can be portrayed as one which takes a low-resolution input image and constructs an up-sampled high-resolution image as the output. Unlike traditional methods (sparse coding-based method, bicubic method) that handle each component separately, this method aims to optimize all the layers at once. Furthermore, for assuaging the vanishing gradient problem that is common to very deep networks, Dense-skip-connections are employed. These enable the building of shorter paths directly within multiple layers.

Qingyuan Zhao, Xin Du, Yaobing Lu, "Aircraft Target Classification Based on CNN", in *IEEE,2020*. The idea of deep learning to aircraft targets recognition based on time frequency diagram. Firstly, we introduced application of Convolutional Neural Network (CNN), and the 4 methods of radar target recognition. Secondly, Short Time Fourier Transformation (STFT) was introduced. Thirdly, the structure of improved LeNet CNN was described, considering the character of radar echo wave. Fourthly, 4 kinds of aircraft targets were introduced. Then, the algorithm based on CNN and STFT was validated based on measured data, and was compared with Support Vector Machine.

Bing Wang, an Zhou, Huainian Zhang, Ning Wang, "An Aircraft Target Detection Method Based on Regional Convolutional Neural Network for Remote Sensing Images", in *IEEE,2019*. Deep residual network to extract the characteristics of aircraft targets, studies and analyzes the size of different aircraft targets, and uses K-means to cluster different sizes. The cluster centers are representative aircraft sizes. Based on these representative sizes of the aircrafts,

the Aircraft Targets Region Proposal Network (ATRPN) is proposed to synthesize the geometric characteristics of different aircraft.

III. METHODOLOGY

a. Integrated Approach for Aircraft type recognition

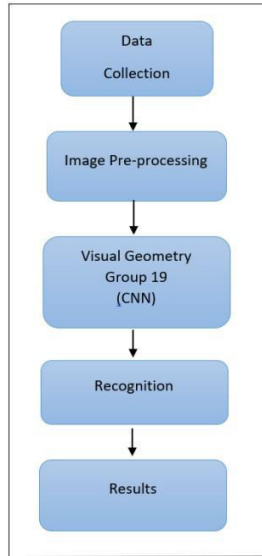


Figure 3.1: The Block Diagram for Aircraft Recognition

b. System Architecture

The Convolutional Neural Network (CNN) architecture incorporates various layers that process and extract features from input images, enabling accurate predictions regarding their class or category. By utilizing convolutional layers, pooling layers, and fully connected layers, the CNN effectively analyzes and interprets the visual information inherent

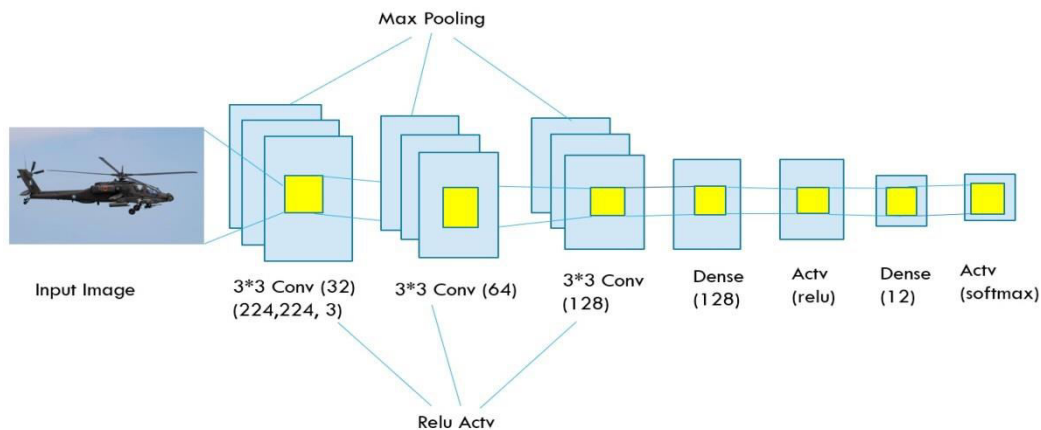


Figure 3.2: System Architecture

in the images. The architecture specifies the number of filters, their sizes, and the activation functions employed in each layer. Additionally, it outlines the input shape and dimensions of the images under consideration. Constructing this CNN architecture facilitates the development of a robust and efficient system capable of classifying images.

The architecture consists of multiple layers that process and extract features from the input images. The overall

structure of the CNN can be described as follows:

The first layer is a convolutional layer with 32 filters of size 3x3. It applies the Rectified Linear Unit (ReLU) activation function to introduce non-linearity. The input shape of the layer is determined by the `img_width` and `img_height` dimensions of the images, with 3 channels representing the RGB color space.

After the convolutional layer, a max pooling layer with a pooling size of 2x2 is added. This layer reduces the spatial dimensions of the feature maps, capturing the most relevant information while reducing computational complexity.

This pattern is repeated twice with subsequent convolutional layers, each employing a larger number of filters (64 and 128, respectively) but maintaining the 3x3 filter size. After each convolutional layer, a max pooling layer is applied.

Next, a flattening layer is added to convert the multidimensional feature maps into a one-dimensional vector, preparing the data for input into the fully connected layers.

The following layer is a dense layer with 128 neurons, employing the ReLU activation function. This layer learns higher-level features by combining the extracted information from the previous layers.

Finally, the output layer is another dense layer with 12 neurons, corresponding to the number of classes in the classification task. The activation function used here is softmax, which outputs a probability distribution over the classes, indicating the likelihood of each input image belonging to a specific class.

Overall, this CNN architecture sequentially applies convolutional, max pooling, flattening, and fully connected layers to capture and process features from input images, ultimately producing class predictions based on the learned representations.

c. Flow Diagram: Model Integration with User Interface

Flask framework is used to integrate the trained model with the user interface. Flask is a web framework written in Python that facilitates the development of web applications and allows for seamless integration with a trained CNN model.

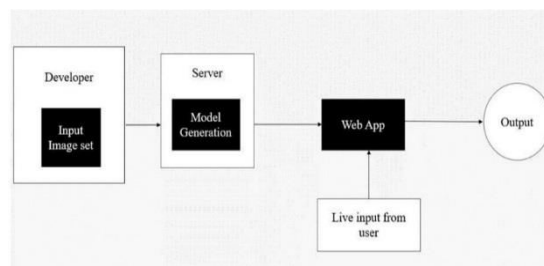


Figure 3.3: Model Integration with User Interface

The Figure 3.3 illustrates the seamless integration process between a trained model and a user interface. Once the model has undergone training, it is saved and integrated with a user interface, using the Flask framework. The resulting website offers users a variety of features, including registration and login functionalities. Users can upload an image to obtain predictions on the aircraft model type. Furthermore, they can browse through a list of previously uploaded images and access a dedicated page to retrieve prediction results for a specific uploaded image.

d. Database Scheme of Tables

The Database has been implemented using SQLyog. SQLyog is a popular graphical user interface (GUI) tool for managing and working with MySQL databases. It is designed to simplify database administration tasks and provide a user-friendly interface for database developers and administrators.

3.4.1 Database Scheme Aircraft Description: The Figure 3.4 stores data for 12 distinct types of aircraft, including the name and description of each aircraft, both of which are of the varchar data type.

name	description
<input type="checkbox"/> Boeing AH-64 Apache	The Boeing AH-64 Apache is an American twin-turboshaft attack helic
<input type="checkbox"/> Dassault Mirage 2000	The Dassault Mirage 2000 is a French multirole, single-engine, four
<input type="checkbox"/> Dassault Rafale	The Dassault Rafale is a French twin-engine, canard delta wing, mul
<input type="checkbox"/> Eurofighter Typhoon	The Eurofighter Typhoon is a European multinational twin-engine, ca
<input type="checkbox"/> HAL Prachand	The HAL Prachand is an Indian multi-role, light attack helicopter d
<input type="checkbox"/> HAL Rudra	The HAL Rudra, also known as ALH-WSI, is an armed version of the HA
<input type="checkbox"/> HAL Tejas	The HAL Tejas is an Indian, single engine, delta wing, light multir
<input type="checkbox"/> Ilyushin Il-78	The Ilyushin Il-78 is a Soviet/Russian four-engined aerial refuelin
<input type="checkbox"/> Mikoyan MiG-29	The Mikoyan MiG-29 is a twin-engine fighter aircraft designed in th
<input type="checkbox"/> Mil Mi-24	The Mil Mi-24 is a large helicopter gunship, attack helicopter and
<input type="checkbox"/> SEPECAT Jaguar	The SEPECAT Jaguar is an Anglo-French jet attack aircraft originall
<input type="checkbox"/> Sukhoi Su-30	The Sukhoi Su-30 is a twin-engine, two-seat supermaneuverable fight
* (NULL)	(NULL)

Figure 3.4: Aircrafts Description

3.4.2 Database Scheme for User Registration: The Figure 3.5 presents the database schema for user registration, which includes columns for username, password, email, mobile, and address.

id	username	password	email	mobile	address
<input type="checkbox"/> 14	Varsha	varsha	varsha@gmail.com	9887776554	hyderabad
<input type="checkbox"/> 15	minnu	minnu	minnu@gmail.com	8472478021	chennai
<input type="checkbox"/> 16	Ram	ram	ram@gmail.com	9887776556	hyderabad
<input type="checkbox"/> 17	kminnu	kminnu	kminnu@gmail.com	8467456801	chennai
* (NULL)	(NULL)	(NULL)	(NULL)	(NULL)	(NULL)

Figure 3.5: User Registration

3.4.3 Database Scheme for Uploaded Images: The Figure 3.6 displays the database schema for uploaded images by users, containing columns for name, image, username (varchar data type), and id (int data type).

id	name	image	username
<input type="checkbox"/> 30		4.jpg	Varsha
<input type="checkbox"/> 31		1.jpg	Varsha
<input type="checkbox"/> 32		5.jpg	minnu
<input type="checkbox"/> 33		1.jpg	Ram
<input type="checkbox"/> 35		5.jpg	minnu
* (NULL)	(NULL)	(NULL)	(NULL)

Figure 3.6: Uploaded Images

IV. RESULTS AND DISCUSSION

e. Implementation

The implementation process of "Deep Learning for Aircraft Recognition Using CNN" includes executing code and training the model within the Jupyter notebook environment. For the user interface/website, the code is written in VS Code, and the connection to the trained model is established using the Flask framework. The dynamic data required for the user interface is stored in a database, which can be conveniently accessed and managed through SQLyog.

4.1.2 Epochs: Epoch refers to a complete pass through the entire training dataset during the training process.

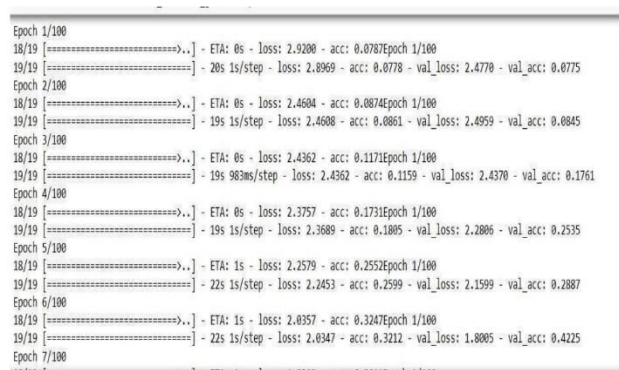


Figure 4.1 Epochs

The Figure 4.1 shows a snippet of training progress of a convolutional neural network model over 100 epochs. Each epoch represents a complete pass through the training data. In each epoch, the model's performance is measured by two metrics: loss and accuracy. Loss represents the error between the predicted output and the true output, and the goal is to minimize this value. Accuracy measures how well the model's predictions match the actual labels.

4.2 Results

A training and validation accuracy graph visually shows the accuracy of a machine learning model on the training and validation datasets. It helps analyze the model's performance and the generalization ability over time.

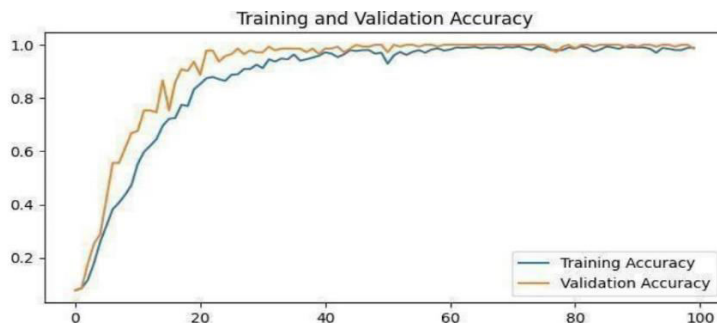


Figure 4.2: Accuracy Graph for Aircraft Recognition

A training and validation loss graph illustrates the loss or error of a machine learning model during the training and validation phases. It helps monitor how effectively the model is learning and making accurate predictions.

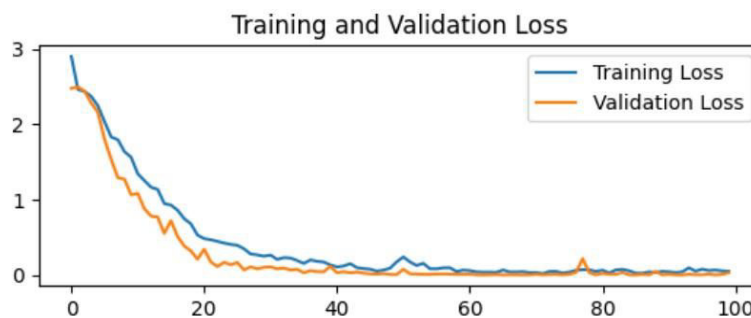


Figure 4.3: Loss Graph for Aircraft Recognition



Figure 4.4: Predicted Result

In the Figure 4.4, the trained model accurately identifies the aircraft type as "Sukhoi Su-30".

V. CONCLUSION

The trained CNN model has practical applications in air traffic control, aviation maintenance, research, education, and training. It aids in automatic aircraft identification for efficient monitoring, assists in maintenance procedures, supports aerodynamics studies, enhances aircraft recognition understanding, and offers accurate aircraft classification. By overcoming manual identification challenges, the model provides a valuable tool in the aviation industry, demonstrating effectiveness and reliability through extensive testing and evaluation.

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