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CNN BASED REALTIME AIRCRAFT DETECTION

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Abstract: ***Deep learning techniques such as Convolutional Neural Networks (CNN) and Transfer Learning are being used to detect and identify fighter aircraft or jets in a dataset consisting of 21 different aircraft with 20,000 images. The principle of "pooling" in Convolutional Neural Networks (CNN) involves progressively reducing the spatial size of the model to decrease the number of parameters and computations in the network. These techniques have been applied to various aspects of aircraft recognition, including object detection and engine defect detection.*** *Convolutional Neural Networks (CNNs) are widely employed in various domains, including defence, agriculture, business, and face recognition technology, for image detection tasks. Transfer learning is a machine learning method that involves using a pre-trained model as the initial point for a new task, allowing for faster training and improved performance. This technique is particularly useful in deep learning, where large amounts of data are required for training complex models. The dataset is processed using Python libraries such as pandas, seaborn, and sci-kit-learn to find pre-trained patterns and insights. The data is then split into training and testing datasets, with 80% and 20% of the total data, respectively. A model is built using the TensorFlow library for CNN, and the metric used is "accuracy". Additionally, a transfer learning model is built to compare the accuracy results and adopt the best-fitting one.*

Keywords: ***Convolutional Neural Network, Deep Learning, Artificial Neural Network, Support Vector Machines.***

1. INTRODUCTION

The development of fighter aircrafts has been crucial since the 1900s, playing a significant role in both World Wars and leading to the victory of the sides with more and powerful aircrafts. Billions of dollars have been spent on the advancement of fighter aircrafts or jets. Deep Learning has shown its potential in various fields by handling vast amounts of data with the help of neural networks, making it more efficient than classic machine learning algorithms. One application of Deep Learning is detecting and classifying fighter aircrafts using Convolutional Neural Networks (CNN) and transfer learning. The traditional method of detecting aircraft is through RADAR, which, although efficient, can be costly and time-consuming on a large scale with a massive number of aircrafts.

Deep Learning has proven to significantly reduce the cost and workforce required for a particular task through conventional processes. Deep learning neural networks use an aggregate of records inputs, weights, and bias to attempt to work the same as the human mind.

The project aims to improve accuracy and speed in aircraft detection by utilizing a CNN structure for training and object detection. One of the primary challenges in detecting aircraft images is the similarity between the background and aircraft, compounded by the small appearance of aircraft due to the altitude at which images are taken. An example application involves the detection and classification of fighter aircraft using CNN and transfer learning.

A Convolutional Neural Network (CNN) is a type of artificial neural network that is widely used in image processing, pattern recognition, and computer vision tasks. CNNs are designed to automatically and adaptively learn spatial hierarchies of features from images, making them highly effective in tasks such as object detection, image recognition, and image segmentation. CNNs consist of multiple layers, including convolutional layers, pooling layers, and fully connected layers.

Artificial Neural Networks (ANNs) emulate the brain's structure with interconnected nodes. They're trained using algorithms like back propagation to minimize errors, finding applications in diverse fields such as image recognition and finance for tasks like pattern recognition and classification.

Support Vector Machines (SVMs) are powerful supervised machine learning models used for classification tasks. They work by finding an optimal hyperplane that maximizes the margin between different classes of data points, enabling accurate classification. SVMs can handle linear and nonlinear data through the kernel trick, making them versatile for various applications. Feature selection is crucial for SVM performance, with support vectors playing a key role in determining the optimal hyperplane. SVMs are widely used in text classification and other domains where accurate classification is essential.

2. LITERATURE SURVEY

[1] Zhi-Ze Wu, Thomas Weise, Yan Wang, Yongjun Wang, "Convolutional Neural Network Based Weakly Supervised Learning for Aircraft Detection from Remote Sensing Image", 2020.

This research explores CNNs for aircraft detection in remote sensing images via weakly supervised learning, sidestepping precise annotations. It aims to create a framework for spotting aircraft accurately without detailed labels, potentially improving efficiency and cost-effectiveness in aerial monitoring and surveillance.

[2] Ting Wang, Xiaodong Zeng, Changqing Cao, Zhejun feng, JinWu, Xu Yan, Zengyan WU, "Aircraft Detection in Remote Sensing Images Based on Lightweight Convolutional Neural Network", 2022.

This study explores aircraft detection in remote sensing images using a lightweight Convolutional Neural Network (CNN). It aims to develop a model capable of swiftly and accurately identifying aircraft in such imagery, crucial for resource-constrained settings prioritizing computational efficiency. By addressing the challenges of aircraft detection in remote sensing, this research aims to enhance the effectiveness of aerial monitoring and surveillance applications.

[3] Ferhat Ucar, Besir Dandil, Fikret Ata, "Aircraft Detection System Based on Regions with Convolutional Neural Networks", 2020.

This study combines region-based techniques with CNNs for aircraft detection, boosting accuracy and efficiency in diverse conditions to enhance aerial monitoring and surveillance.

[4] Jinsheng Ji, Tao Zhang, Zhen Yang, Linfeng Jiang, Weilin Zhong, Huilin Xiong, "Aircraft Detection from Remote Sensing Image Based on A Weakly Supervised Attention Model", 2019.

The study presents a new aircraft detection technique in remote sensing images employing a Weakly Supervised Attention Model, improving accuracy and efficiency in aerial monitoring and surveillance. This method offers insights into aircraft presence without requiring extensive annotations.

3. PROPOSED SYSTEM

The proposed system begins by preprocessing images to ensure uniformity and enhance processing efficiency. This includes resizing all images to a standard resolution of 80x80 pixels and normalizing them to a range of 0-1. These steps are crucial as neural networks require inputs of the same size, and normalization helps in reducing time consumption during processing.

For the dataset, the Multi-type Aircraft Remote Sensing Images (MTARSI) dataset is utilized, containing 9,385 images of 20 aircraft types. Classes with repeated types are excluded to streamline the dataset and avoid redundancy in the model.

Data augmentation techniques are applied to generate additional training images, including random rotation, shifts, shear, and flips. This augmentation process enhances the model's ability to generalize to unseen data and improve overall performance.

The CNN model is constructed with various parameters, including different hidden layers, input layers, activation functions, and loss functions. Hyperparameter tuning is performed to optimize the model's performance further. Transfer learning algorithms, specifically VGG16, are

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also employed, with only a certain number of hidden layers being trained and tested to enhance efficiency.

Finally, the accuracies of the developed CNN algorithm and the transfer learning models are compared. After increasing filters and nodes in dense layers and through hyper parameter tuning, a final model with higher accuracy is achieved. Initial models may show low accuracies for certain classes, indicating the need for improvement. However, with the adjustments made, the final model demonstrates improved performance and is deemed suitable for further evaluation.

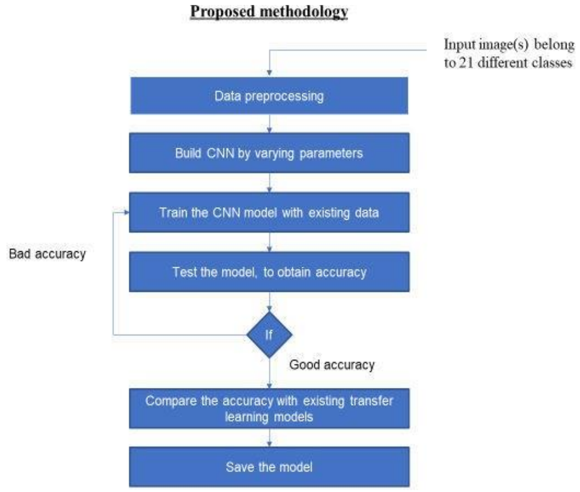

Fig 1: System Architecture

3.1 ALGORITHMS USED

Convolutional Neural Network:

A Convolutional Neural Network (CNN) is an algorithm of deep learning that is particularly best-suited for image recognition and image processing tasks. It is made up of multiple layers, including pooling layers, convolutional layers, and fully connected layers.

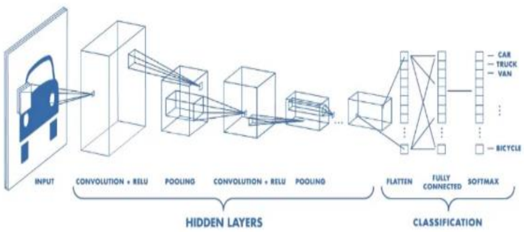

Fig 2: Convolutional Neural Network

Convolutional Neural Networks (CNNs) are modeled after the visual processing in the human brain, and their architecture is adept at capturing hierarchical patterns and spatial dependencies within images. They are designed to mechanically and adaptively examine spatial hierarchies of functions from enter data.

Transfer Learning:

Transfer learning refers to method in machine learning where a model trained for one specific task is leveraged as the initial foundation for a model intended for another distinct task. Transfer learning is a valuable technique in machine learning, this approach is advantageous when the second task is akin to the first, or when data for the second task is limited. By leveraging the learned features from the first task, the model can rapidly and effectively learn the second task, thus preventing overfitting by utilizing general features already learned.

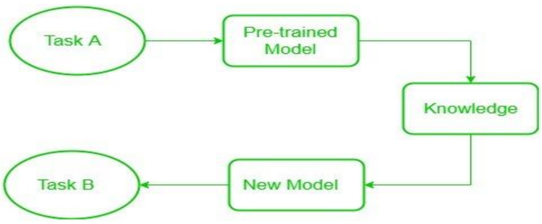

Fig 3: Transfer Learning

Support Vector Machine:

Support Vector Machines (SVMs) are powerful supervised machine learning models used for classification tasks. They work by finding an optimal hyperplane that maximizes the margin between different classes of data points, enabling accurate classification.

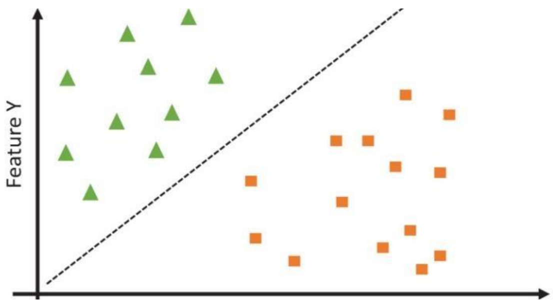

Fig 4: Support Vector Machine

SVMs can handle linear and nonlinear data through the kernel trick, making them versatile for various applications. Feature selection is crucial for SVM performance, with support vectors playing a key role in determining the optimal hyperplane. SVMs are widely used in text classification and other domains where accurate classification is essential.

3.2 LIBRARIES USED

Tensor Flow:

TensorFlow is a freely available open-source software library designed for dataflow programming, supporting machine learning applications like neural networks. Developed by Google, it is used for research and production and offers a versatile platform for developing, training, and deploying machine learning models. TensorFlow's modular architecture enables efficient handling of computational graphs, supporting various hardware accelerators and high-level APIs for easy model creation. It is widely used in various real-world applications, including image recognition, natural language processing, healthcare, autonomous vehicles, finance, and gaming.

Numpy:

NumPy is a versatile Python package essential for scientific computing, offering a high-performance multidimensional array object and tools for efficient array manipulation. It serves as a fundamental tool for mathematical operations, data analysis, and integration with databases, making it a cornerstone in various fields such as finance, statistics, and linear algebra.

Pandas:

Pandas is a library of Python for data manipulation and analysis, offering high-performance tools for data loading, preparation, manipulation, modelling, and analysis. It is widely used in various fields, including academia and industry, for data-driven tasks such as finance, economics, statistics, and analytics. Pandas provides powerful data structures like Data Frames, enabling efficient data handling, cleaning, and merging.

Matplotlib:

Matplotlib is a Python library used for 2D plotting that produces high-quality figures in various formats and

interactive environments. It simplifies plotting tasks, offering a MATLAB-like interface and an object-oriented interface for advanced users. Matplotlib is widely used by scientists and developers for creating plots, histograms, scatter plots, and more with minimal code. A user community actively contributes to its development and support.

Skikit - Learn:

Scikit-learn is a versatile Python library for machine learning, offering a comprehensive suite of supervised and unsupervised learning algorithms with a consistent interface. Licensed under a permissive BSD license, it is widely used in academic and commercial settings. Scikit-learn provides tools for classification, regression, clustering, and model selection, making it a popular choice for data analysis and machine learning tasks due to its seamless integration with other Python libraries.

3.3 TECHNOLOGIES USED

Python:

Python is a widely used programming language known for its simplicity, readability and flexibility. Created by Guido van Rossum and first released in 1991, Python has become one of the most popular languages in the world. The design concept features easy-to-read code and syntax that makes it easy to learn and use. Python supports a variety of programming paradigms, including methods, object-oriented, and functional programming, allowing developers to choose the approach that best suits their needs. One of the best features of Python is its ability to handle data input/output, communication, web development, database interaction, etc. It is a comprehensive library that provides many models and patterns for operations. Suite, discounted. The need for external dependency. In addition, Python's strong and active community continues to develop and maintain a wide range of third-party libraries and frameworks to meet the needs of various types of applications, including data science, machine learning, web development, visualization, and automation.

Machine Learning Model Training:

The model is trained by using various machine learning algorithms like Convolutional Neural Network, Transfer

Learning, Support Vector Machine. With these algorithms we achieved an accuracy of 99% which is the best improvement of the existing system.

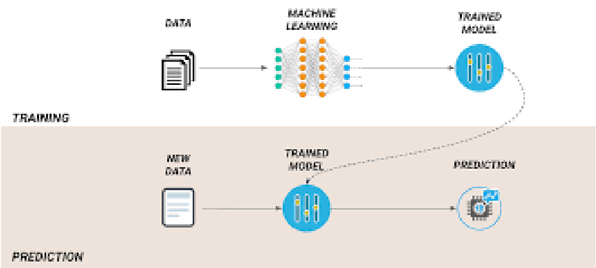

Fig 5: Machine Learning Model Training

3.4 RESULTS & ANALYSIS

The images from MTRSAI datasets are given in the below Figures respectively.

Fig 6: Sample Images from Data Set

The proposed method is implemented with Keras using python. The number of epochs is set as 25; batch size is selected as 16. The learning rate of the network is set at 0.0004. The gradient descent optimization algorithm is used. The results obtained are given in Table 2 and are compared against results obtained with flight detection using Basic CNN Model.

S.no	Method	Accuracy
1.	Basic CNN model (First Model)	79.38
2.	Proposed Method Using CNN (VGG16)	99.4

Table 1: Accuracy of Models

The provided figure shows the results obtained during the training phase of a machine learning model.

```
Epoch 16/25
470/470 [==============================] - 25s 53ms/step - loss: 8.8455 - accuracy: 0.9923 - val_loss: 8.8128 - val_accuracy: 0.9827 - lr: 2.1952e-05
Epoch 17/25
470/470 [==============================] - 26s 55ms/step - loss: 8.2278 - accuracy: 0.9941 - val_loss: 8.0674 - val_accuracy: 0.9540 - lr: 1.9863e-05
Epoch 18/25
470/470 [==============================] - 25s 53ms/step - loss: 7.6523 - accuracy: 0.9961 - val_loss: 7.5195 - val_accuracy: 0.9607 - lr: 1.7973e-05
Epoch 19/25
470/470 [==============================] - 25s 53ms/step - loss: 7.1690 - accuracy: 0.9912 - val_loss: 7.0824 - val_accuracy: 0.9560 - lr: 1.6263e-05
Epoch 20/25
470/470 [==============================] - 25s 53ms/step - loss: 6.7264 - accuracy: 0.9963 - val_loss: 6.6822 - val_accuracy: 0.9447 - lr: 1.4715e-05
Epoch 21/25
470/470 [==============================] - 26s 56ms/step - loss: 6.3310 - accuracy: 0.9971 - val_loss: 6.2908 - val_accuracy: 0.9474 - lr: 1.3315e-05
Epoch 22/25
470/470 [==============================] - 26s 56ms/step - loss: 5.9715 - accuracy: 0.9971 - val_loss: 5.9210 - val_accuracy: 0.9620 - lr: 1.2048e-05
Epoch 23/25
470/470 [==============================] - 26s 56ms/step - loss: 5.6279 - accuracy: 0.9983 - val_loss: 5.5878 - val_accuracy: 0.9600 - lr: 1.0901e-05
Epoch 24/25
470/470 [==============================] - 26s 56ms/step - loss: 5.3071 - accuracy: 0.9988 - val_loss: 5.2964 - val_accuracy: 0.9554 - lr: 9.8639e-06
Epoch 25/25
470/470 [==============================] - 26s 56ms/step - loss: 5.0017 - accuracy: 0.9989 - val_loss: 4.9776 - val_accuracy: 0.9580 - lr: 8.9252e-06
```

Fig 7: Sample Image from Code Output

The experimental results for PCA and the proposed method using CNN with transfer learning in terms of classification accuracy are given in Table 2. It is inferred from the results that the proposed method of flight recognition using CNN with Input Layer+2x (Convolution Layer + ReLU) Input Size224x224x3 Max Pooling Layer 2 x (Convolution Layer withReLU) Max Pooling Layer 3 x (Convolution Layer with ReLU) Max Pooling Layer 3 x (Convolution Layer with ReLU) Max Pooling Layer 3 x (Convolution Layer with ReLU) 2x (Fully Connected Layer+Drop out+ReLU) Max Pooling Layer Fully Connected Layer + SoftMax + Output Layer. transfer learning achieves better classification accuracy compared to the method used in the first model. It achieves 99.4% accuracy for MTARSI database Aircraft images.

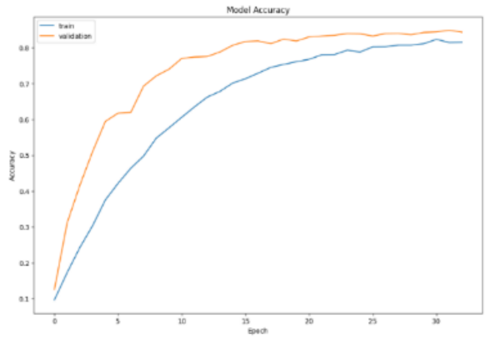

Fig 8.1: Accuracy Graph for Model

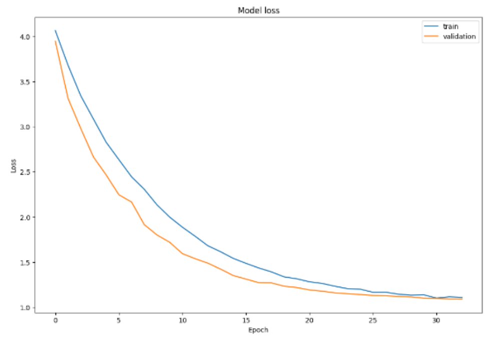

Fig 8.2: Loss Graph for Model

4. CONCLUSION

This paper introduces an automated aircraft recognition method leveraging the VGG16 CNN model pretrained on ImageNet. The weights of the model are initialized with ImageNet parameters and fine-tuned on a dataset of aircraft images. During training, features are extracted and utilized by a fully connected layer with a SoftMax activation function for classification. The method is evaluated on publicly available MTARSI aircraft datasets, achieving a flight recognition accuracy of 99.4% for MTARSI flight images. Experimental results highlight the superiority of CNN with transfer learning over other methods in flight detection and classification accuracy.

Classes that are predicted with high accuracy by the model.The model can be relied upon for accurate tagging without any manual intervention.

- B-1
- B-2
- E-3
- F-22
- type12(C-21)
- type-17(P-63)
- type-18(F-16)
- type-19(T-6)
- type-20(B-29)
- type-21(t-43)

We achieved an accuracy of 99.4 percent which is far better compared to the first model.

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[4] Jinsheng Ji, Tao Zhang, Zhen Yang, Linfeng Jiang, Weilin Zhong, Huilin Xiong, **“**Aircraft Detection from Remote Sensing Image Based on A Weakly Supervised Attention Model**”**, 2019.

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