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Fighter Aircraft Detection using CNN and Transfer Learning

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Abstract: *In this work, Deep learning techniques such as Convolutional Neural networks (CNN) and Transfer Learning are used to detect and identify Fighter aircraft or jets. A dataset consisting of 21 different aircraft with 20000 images is being processed using the above algorithms. CNN works on the principle of "pooling," which progressively reduces the spatial size of the model to decrease the number of parameters and computations in the network. CNN's are widely used for image detection in different domains, including defense, agriculture, business, face recognition technology, etc. Transfer learning is a machine learning method where a model created for a task is reused as the initial point for a model on a second task. Transfer learning is related to issues such as multi-task learning and concept drift and is not only an area of study in deep learning. The dataset is processed and uses python libraries such as pandas, seaborn, sci-kit- learn, etc., to find any pre-trained patterns and insights. Data is separated into train and test datasets with 80-20 percent of total data, respectively. A model is built using the TensorFlow library for CNN. The metric used is "accuracy." A transfer learning model is also built to compare the accuracy results and adopt the best-fitting one.*

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

I. INTRODUCTION

Fighter plane detection from far-off sensing snapshots is small goal popularity beneath neath an extensive range. It has issues. However, one is the performance of large-place picture detection; the alternative is the Fighter plane function extraction and expression in complicated conditions. Nevertheless, the growth of high-decision far-off sensing snapshots has definitive studies on this place. The essential factor of goal detection is to discover the solid goal function. Traditional plane detection techniques specify awareness of function description, function selection, function extraction, and different algorithms. Adjustment and optimization of rules can enhance detection accuracy and performance. However, those functions are not unusual to place picture attributes; thus, it's miles tough to fundamentally differentiate between goal and heritage [1]. Moreover, in a complicated environment, the technical accuracy is poor, consisting of the histogram of the oriented gradient (HOG) [7] and scale-invariant function transform (SIFT). Some research matched the check picture by designing a fashionable goal pattern [2, 8]. However, this technique applies to memorable scenes; it isn't very versatile. In practice, the multi-function fusion technique is frequently used to describe the goal [9] comprehensively. Nonetheless, it will increase the complexity of the rules and decrease the detection performance to a few extent [7, 10]. The deep getting to know a technique has a function-extraction strong ability. Through a multilayer neural community and plenty of samples, it extracts the multilevel functions of objects. The method has a superior drastically in herbal picture processing [11, 12]. Furthermore, several high-overall performance algorithms [13], consisting of the Region Convolutional Neural Network (R-CNN) and Fast and Faster R-CNN, had been proposed. However, those techniques require many samples to teach the community version. Many invalid place proposals ought to be detected; that's inefficient. Some goal detection techniques, the use of far-off sensing snapshots primarily based totally on deep getting to know, had been presented. Weakly supervised and semi-supervised function getting-to-know methods had been proposed. Zhang et al. proposed a plane detection technique based totally on weakly supervised getting-to-learn coupled with a CNN. Han et al. proposed an iterative detector approach, through which the detector has iteratively educated the use of delicate annotations till the version converges. Nevertheless, a non-convergence scenario can also occur, reducing detection accuracy. Weakly supervised getting to know extracts functions with a small quantity of pattern data. However, the components aren't enough because of a loss of samples. Therefore, the detection accuracy is limited. The deep studying technique has 3 essential troubles in plane detection from far-flung sensing pix: Limited schooling samples. They are using a small number of samples to teach a high-accuracy version. Aircraft in far-flung sensing pix have apparent functions, and a few balance functions may be decided on as constraint conditions. Combining those functions with deep studying, the detection technique will be more focused on ability. A far-flung sensing photograph covers a massive area, its scale isn't uniform, and the sensor is miscellaneous. The present deep studying version and community shape aren't without delay appropriate for far-flung sensing photograph plane detection. [3].

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The community shape and detection set of rules have to be changed to enhance performance and accuracy. Because of the above troubles, a cascade CNN (CNN) structure is proposed to improve accuracy and performance. It carries four principal parts: (1) A two-stage CCNN is designed to rapidly technique far-flung sensing photograph plane detection. The first-stage community quickly classifies the scene and removes the regions that don't include planes. The second-stage community identifies and locates planes within the areas now no longer filtered out within the preceding step. (2) A switch studying technique is used to fine-track the parameters of pre-skilled class and item detection fashions with the samples. (3) A place thought filtering technique of a characteristic geometrical constraint (GFC) primarily based totally on the geometric functions of the plane is proposed. By using those functions to clear out the place proposals, several non-plane place proposals are eliminated. (4) A plane pattern library and a far-flung sensing photograph-scene pattern library are established. They are used as the data source of transfer learning.

II. CNN TRANSFER LEARNING DEVELOPMENT

A. CNN

Convolutional Neural Networks (CNN) have completely ruled the machine vision area in current years. A CNN includes an enter layer, an output layer, and a couple of 3 hidden layers. The hidden layers usually encompass convolutional, pooling, wholly linked, and normalization layers (Re LU). Additional layers may be used for extra complicated models. Examples of an average CNN may be visible in [5], depicted in Figure 1. The CNN structure has proven notable overall performance in many Computers Vision and Machine Learning problems. CNN trains and predicts at a summary level, leaving the info for later sections. This CNN version is used significantly in current Machine Learning packages because of its ongoing record-breaking effectiveness. Linear algebra is the premise for the way those CNNs work. Matrix vector multiplication is on the coronary heart representing data and weights [12]. Each layer consists of a distinct set of traits for an image set. For instance, if a flight photo is an entrance right into a CNN, the community will examine factors consisting of edges, bright spots, darkish spots, shapes, etc., in its preliminary layers. The subsequent layers will encompass figures and items referring to the recognizable image, consisting of eyes, nose, and mouth. The next layer includes components that seem like real flight, consisting of shapes and items, which the community can outline as a human flight. CNN fits elements instead of the complete photo, breaking the photo class manner into smaller pieces (functions) [13]. A 3x3 grid is described to symbolize the functions extraction via way of means of the CNN for evaluation. The following filtering method includes lining the element with the photo patch. One via the form of means of one, every pixel is expanded via way of means of the corresponding function pixel. As soon as completed, all of the values are summed and divided via the entire range of pixels within the function space. The last fee for the function is then positioned into the function patch. This manner is repeated for the final function patches observed by attempting each possible match- repeated utility of this filter called a convolution. The subsequent layer of a CNN is called "max pooling," which includes shrinking the image stack. To pool an image, the window length should be described (e.g., typically 2x2/3x3 pixels), and the stride should also be determined (e.g., 2 pixels). The window is then filtered across the image in strides, with the max value being recorded for each window. Max pooling reduces the dimensionality of every characteristic map while preserving the maximum important information. The normalization layer of a CNN, also referred to as the Rectified Linear Unit (Re LU), entails converting all terrible values within the filtered photo to 0. This step is then repeated on all of the filtered images; the Re LU layer will increase the non-linear houses of the model. The next step using the CNN is to stack the layers (convolution, pooling, Re LU) so that the output of 1 layer will become the enter of the next. Layers may be repeated, ensuing in a "deep stacking." The last layer within the CNN structure is the ultimately linked layer, also called the classifier. Each cost receives a vote on figuring out the photo classification within this layer. Fully linked layers are regularly stacked together, with every intermediate layer balloting on phantom "hidden" categories. In effect, every extra layer lets the community study even additional state-of-the-art combos of capabilities in the direction of higher decision-making [6]. The values used for the convolution layer and the weights for the ultimately linked layers are received via backpropagation, which is accomplished using the deep neural community. Backpropagation is wherein the neural community uses the mistake withinside the very last solution to decide how many the community adjusts and changes.

B. Transfer learning

Transfer Learning is a Machine Learning approach wherein a version is educated and advanced for one challenge and is then re-used on a 2nd associated challenge. It refers to the state of affairs wherein what has been found in a single place is exploited to enhance optimization in some other environment [8]. Transfer learning is usually carried out when a brand-new dataset is smaller than the original dataset used to teach the pre-trained version [9]. This paper proposes a machine that makes use of a performance (VGG16), which become first delivered on a base dataset (ImageNet) and is now being repurposed to examine functions (or switch them) to learn on a brand-new dataset (CIFAR-10 and Caltech Faces). Regarding the preliminary training, Transfer Learning lets us begin with the found out functions at the ImageNet dataset and modify those functions and possibly the shape of the version too in the condition the brand new dataset/challenge in preference to growing the gaining knowledge of procedure at the statistics from scratch with random weight initialization. TensorFlow is used to facilitate Transfer Learning of the CNN pre-educated version. We observe the topology of the CNN structure to discover an appropriate arrangement, allowing photograph category thru Transfer Learning.

While checking out and converting the community topology (i.e., parameters) and dataset traits to assist decide which variables affect category accuracy, eleven though with constrained computational power and time.

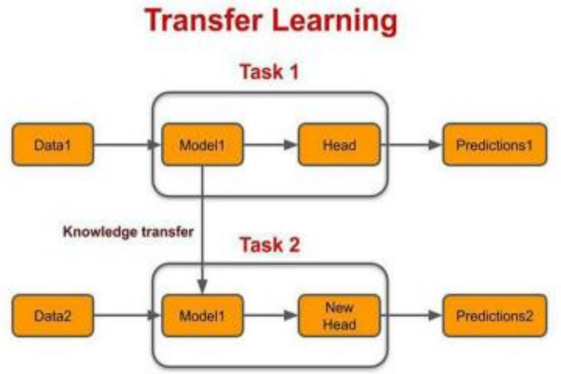

Fig 1

III. PROPOSED METHODOLOGY

Initially, before inputting images into the CNN model we need to pre-process the images:

• Pre-processing includes 2 steps; Resizing all images to the same resolution because the neural networks cannot input images with different resolutions. Finding the resolution of the images to resize the dataset accordingly. Neural networks receive inputs of the same size, all images need to be resized to a fixed size before inputting them to the CNN [14].

• For this purpose, we selected a resolution of 80 X 80 as an input for our model, since there were images with varied resolutions, we picked the image with minimum resolution rather than padding the lower resolution images.

• Normalizing inputs in the range of 0-1 to ease the processing and reduce time consumption

• Then we build the CNN model and train data. Then we test the model to get accuracy

• We compare the accuracy to existing models and save the best model

•We calculate the time consumption of a model

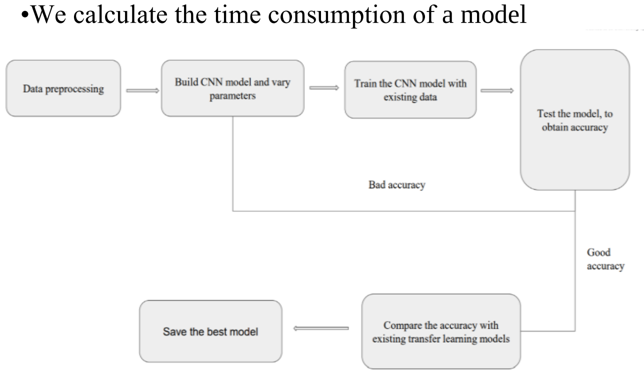

Fig. 2. Block Schematic representation of the proposed study

a) Image Database

We used the Multi-type Aircraft Remote Sensing Images (MTARSI) dataset[6], which became created by Wu et al. (2020). It includes 9,385 photographs of 20 plane types. It has become designed to be a benchmark for plane recognition of the usage of CV. While a number of the pictures have been received from Google images, most of them have been synthetic: they have been created by superimposing planes on distinct backgrounds and acting transformations on them.

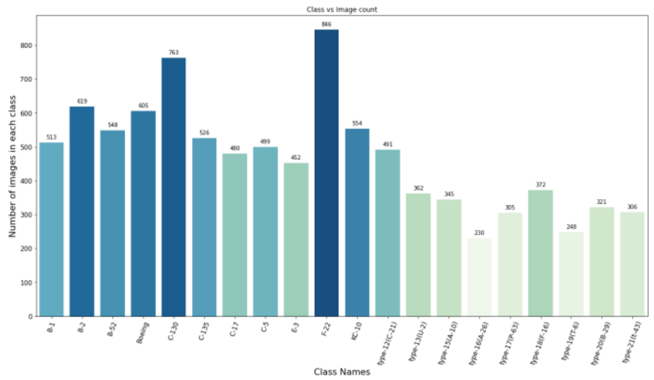

Fig 3

b) Data Preprocessing

The multi-type Aircraft Remote Sensing Images (MTARSI) dataset has 9385 images of 20 aircraft types. This dataset has changed backgrounds, various resolutions, and different poses of aircraft. Classes: type-12, 13, 14, 15,16,17,18,19,20,21 are repeated classes. So, we have excluded these classes during our model building. We find that few images for all classes are synthetically generated by changing the backgrounds from background images. Neural networks get hold of inputs of equal size; all images want to be resized to a set size earlier than inputting them to the CNN. For this purpose, we decided on a decision of 80 X 80 as an entry for our model; considering that there have been images with numerous resolutions, we picked the picture with the minimal solution in preference to padding the decreased resolution images. This 80 X 80-pixel image is sufficient to classify the aircraft visually by humans, so we standardize our dataset to the exact resolution.

c) Data Augmentation

It creates training images thru specific methods of processing or a mixture of multiple processing, together with random rotation, shifts, shear, flips, etc. Image Data Generator. An augmented image generator may be without difficulty created by the usage of Image Data Generator API in Kera's. Image Data Generator generates batches of image data with real-time data augmentation. The maximum fundamental codes to create and configure Image Data Generator and train deep neural networks with augmented pictures are as follows.

```
datagen = ImageDataGenerator()
datagen.fit(train)
X_batch, y_batch = datagen.flow(X_train,
y_train, batch_size=batch_size)
model.fit_generator(datagen,
samples_per_epoch=len(train),
epochs=epochs)
```

Figure 4: image generator code snippet

d) Building CNN with Various Parameters

A CNN algorithm that contains different hidden layers and input layers will be developed. The development also involves modeling the algorithm with different activation and loss functions. The perfect activation and loss function will be concluded after comparing the accuracies We varied the following parameters:

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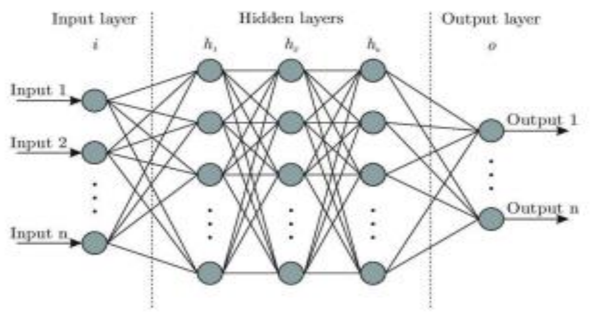

Figure 3.3: Parameters of CNN

e) Modeling the Transfer learning algorithm

Transfer learning algorithms, namely VGG16, will be modeled as per the requirements of the classification algorithm. Not all the layers in the transfer learning models are trained. This will blackout the system used [15]. Only a certain number of hidden layers will be trained and tested.

```
[ ] # Initialise model
    model = Sequential()

    # Block 1
    model.add(Conv2D(filters=32, kernel_size=(3,3), activation='relu', padding='same', kernel_regularizer=L2(l2=0.01), in
    model.add(MaxPool2D(pool_size=(2,2)))
    model.add(BatchNormalization())

    # Block 2
    model.add(Conv2D(filters=64, kernel_size=(3,3), activation='relu', padding='same', kernel_regularizer=L2(l2=0.01)))
    model.add(MaxPool2D(pool_size=(2,2)))
    model.add(BatchNormalization())

    # Block 3
    model.add(Conv2D(filters=64, kernel_size=(3,3), activation='relu', padding='same', kernel_regularizer=L2(l2=0.01)))
    model.add(MaxPool2D(pool_size=(2,2)))
    model.add(BatchNormalization())

    # Block 4
    model.add(Conv2D(filters=64, kernel_size=(3,3), activation='relu', padding='same', kernel_regularizer=L2(l2=0.0001)))
    model.add(MaxPool2D(pool_size=(2,2)))
    model.add(BatchNormalization())

    # Dense
    model.add(Flatten())
    model.add(Dense(32, activation='relu'))
    model.add(Dropout(0.5))
```

Figure 5: Architecture of Transfer Learning Model

f) Comparing the accuracies and final model

The developed CNN algorithm and the transfer learning models are compared using the accuracies, and a final model with high accuracy will be finalized.

For the first model:

The model is not properly trained so we got a difference in class accuracy for each class

Figure 3.5: Accuracy for different classes - MODEL 1 Figure 3.5: Accuracy for different classes - MODEL 1

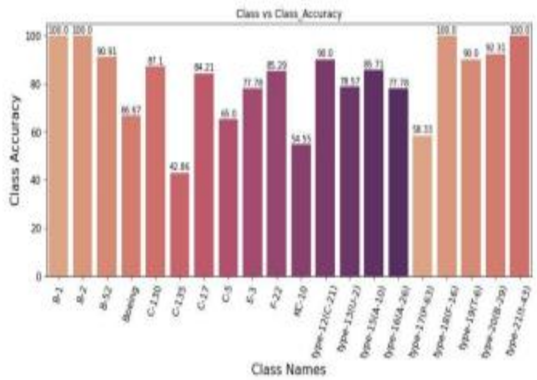

Figure 6: Accuracy for different classes - MODEL 1

Accuracies are very low for a few classes like C-17, C-135, and C-5. So, this model is not suitable for further evaluation.

For the Final model:

After increasing filters and nodes in dense layers and through hyperparameter tuning we are able to obtain higher accuracy for our model.

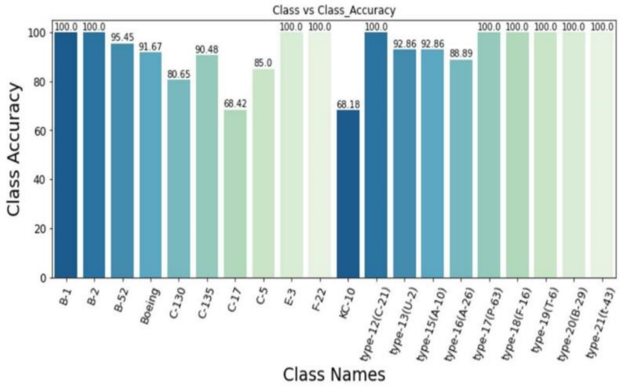

Figure 7: Accuracy for different classes - MODEL 2

IV. CONVOLUTIONAL NEURAL NETWORK (CNN) AND TRANSFER LEARNING

Deep mastering is one of the regions of machine learning that learns representations from information, emphasizing successive layers of more and more significant expressions. The wide variety of layers that contribute to the records is referred to as the intensity of the model. The neural community incorporates the enter layer, a couple of hidden layers, and the output layer. The wide variety of layers that contribute to the information is referred to as the intensity of the model. Convolutional Neural Networks are neural networks that rent convolution operation in matrix multiplication withinside the convolutional layers. The convolution operation is denoted as given withinside the equation. In equation (1), is the entrance is the clear-out kernel and is the output referred to as function map [7]. CNN includes 3 stages. In the primary stage, multiple convolutions have finished using filters to provide a fixed of linear activations. In the second stage, a nonlinear activation, for example, the rectified linear activation characteristic, is finished to output the enter if tremendous and 0 otherwise. In the third stage, the pooling operation is used to lessen the scale of the function map. Some pooling capabilities are max pooling which reveals and replaces with the most cost in a square window, common pooling, which replaces with the common of all of the values withinside the square window, weighted common pooling, and others. At the quit of CNN, the output of the highest pooling layer is given as entering to the completely connected (FC) layer. Every node in the FC layer is attached to all nodes withinside the previous layer. The FC layer plays category into one-of-a-kind classes. The CNNs are skilled thru a procedure referred to as backpropagation which includes four levels – ahead by skip, loss feature, backward by skip, and weight replace. The clear-out weights are initialized randomly.

During the early by skip, the schooling snapshots are surpassed to the community. The mistakes charge has calculated the usage of the loss feature, which compares the community output with the preferred result. Then lower back by skip, and weight replaces levels take location primarily based totally on the mistake charge.

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The backpropagation procedure is repeated for numerous iterations until convergence occurs.
Transfer learning is a machine learning technique in which the understanding received from a specific assignment is transferred to enhance the procedure of mastering any other associated task. The CNN architectures like VGG, Res Net, Alex Net, etc., are already educated at the extensive photograph database of ImageNet, such as extra than 1 million classified high-decision photos belonging to a thousand classes. In this way, the understanding gained from one assignment is transferred to mastering a brand-new assignment. Transfer mastering is mainly used in which there may be a loss of enough schooling data. It suggests proper overall performance in class, and additionally, the computational complexity is significantly decreased because the procedure wants now no longer begins from scratch[12].

CNN Architecture

In the proposed method, the VGG16 CNN structure is used for transfer learning and is skilled at the enter images from Fig. 1 VGG16 Architecture the aircraft dataset. The input images to the CNN are of length 224x224x3. The input images are exceeded thru a stack of thirteen convolutional layers with a clear-out length of 3x3 and one-of-a-kind depths of 64,528,256 and 512. 3 completely related layers (FC) are used following the convolutional layers. The first FC layers have 4096 devices, and the remaining FC layer plays classification into a thousand classes. All the hidden layers have non-linear rectification (ReLU). The SoftMax layer is used because the remaining layer of the CNN plays the activation function. Including the enter and output layer, there are an absolute of forty-one layers withinside the structure. The structure of the VGG16 CNN version is proven in Figure 1. The VGG16 became skilled on an extensive ImageNet database, and the weights were learned [4]. These weights are used to initialize the version and skilled at the enter aircraft photo training dataset. The extracted functions are fed as entering to the FC layer accompanied by SoftMax activation and categorized into one-of-a-kind aircraft. Input Size 80x80x3

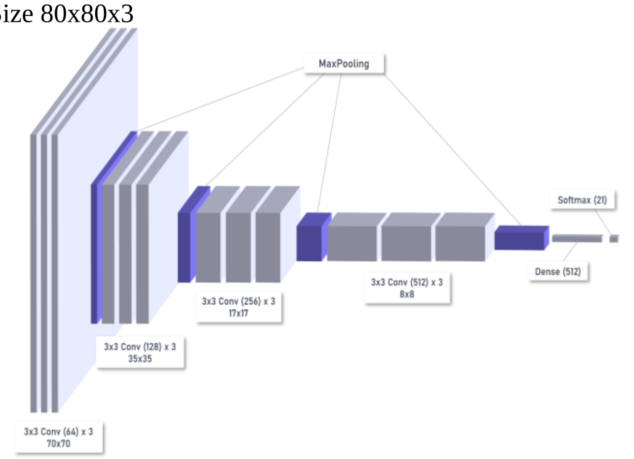

Fig 8

V. RESULTS AND DISCUSSION

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

Figure 9: Sample Images from Dataset

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

The screen capture of the results obtained using training phase is given in Figure 4.

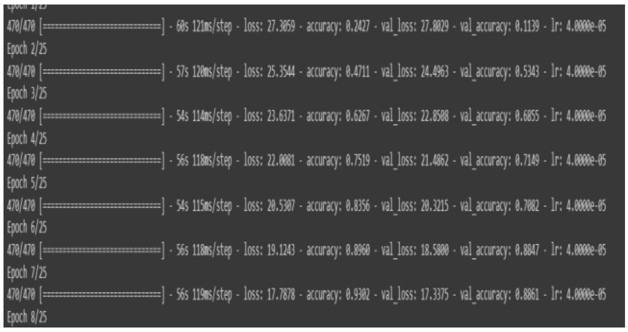
```
470/470 [==========================] - 60s 121ms/step - loss: 27.3059 - accuracy: 0.2427 - val_loss: 27.8029 - val_accuracy: 0.1139 - lr: 4.0000e-05
Epoch 2/25
470/470 [==========================] - 57s 120ms/step - loss: 25.3544 - accuracy: 0.4711 - val_loss: 24.4963 - val_accuracy: 0.5343 - lr: 4.0000e-05
Epoch 3/25
470/470 [==========================] - 54s 114ms/step - loss: 23.6371 - accuracy: 0.6267 - val_loss: 22.8508 - val_accuracy: 0.6855 - lr: 4.0000e-05
Epoch 4/25
470/470 [==========================] - 56s 118ms/step - loss: 22.0081 - accuracy: 0.7519 - val_loss: 21.4862 - val_accuracy: 0.7149 - lr: 4.0000e-05
Epoch 5/25
470/470 [==========================] - 54s 115ms/step - loss: 20.5307 - accuracy: 0.8356 - val_loss: 20.3215 - val_accuracy: 0.7082 - lr: 4.0000e-05
Epoch 6/25
470/470 [==========================] - 56s 118ms/step - loss: 19.1243 - accuracy: 0.8960 - val_loss: 18.5800 - val_accuracy: 0.8847 - lr: 4.0000e-05
Epoch 7/25
470/470 [==========================] - 56s 119ms/step - loss: 17.7878 - accuracy: 0.9302 - val_loss: 17.3375 - val_accuracy: 0.8861 - lr: 4.0000e-05
Epoch 8/25
```

Figure: 10. Sample Images 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 Size 224x224x3 Max Pooling Layer 2 x (Convolution Layer with ReLU) 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.

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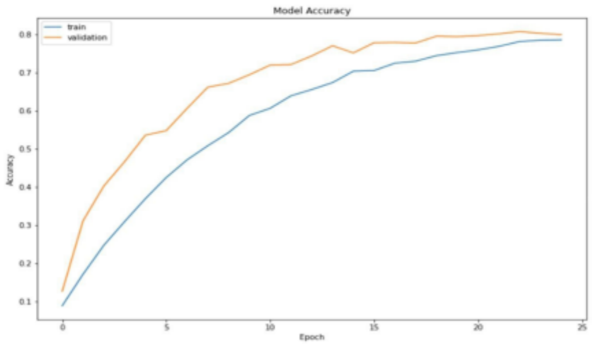

Figure: 11. Accuracy graph for Model 1

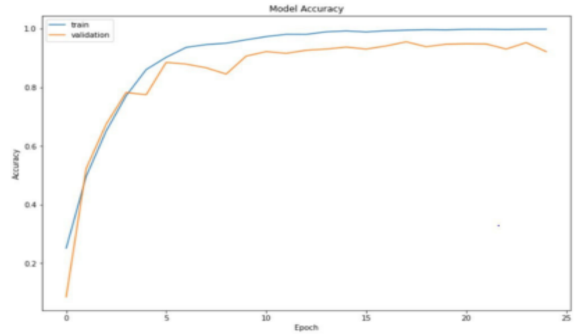

Figure: 11. Accuracy graph for Model 2

VI. CONCLUSION

An automated Aircraft recognition method has been proposed in this paper. The pre-trained CNN model VGG16 which was trained on a huge database of ImageNet is used to initialize the weights and the model is trained on the input aircraft images dataset. The features are extracted during the training phase and fed to the fully connected layer with a SoftMax activation function for classification. The method is tested on publicly available MTARSI datasets of Aircraft. The flight recognition accuracy of 99.4% is achieved for MTARSI database Flight images. The experimental results show that flight detection using CNN with transfer learning gives better classification accuracy in comparison with other methods.

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

APPENDIX

It is optional. Appendixes, if needed, appear before the acknowledgment.

ACKNOWLEDGMENT

It is optional. The preferred spelling of the word "acknowledgment" in American English is without an "e" after the "g." Use the singular heading even if you have many acknowledgments. Avoid expressions such as "One of us (S.B.A.) would like to thank ...." Instead, write "F. A. Author thanks *"Sponsor and financial support acknowledgments are placed in the unnumbered footnote on the first page*.

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