APPLICATION OF DEEP CONVOLUTIONAL NETWORK FOR THE CLASSIFICATION OF AUTO IMMUNE DISEAS

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Astract*—Indirect Immuno Fluorescence (IIF) detection analysis technique is in limelight because of its great importance in the field of medical health. It is mainly used for the analysis of auto-immune diseases. These diseases are caused when body's natural defense system can't distinguish between normal body cells and foreign cells. More than 80 auto-immune diseases exist in humans which affect different parts of body. IIF works both manually as well as by using Computer-Aided Diagnosis (CAD). The aim of research is to propose an advanced methodology for the analysis of auto-immune diseases by using well-known model of transfer learning for the analysis of autoimmune diseases. Data augmentation and data normalization is also used to resolve the problem of over fitting in data. Firstly, freely available MIVIA data set of HEP- type 2 cells has been selected, which contains total of 1457 images and six different classes of staining patterns named as centromere, homogeneous, nucleolar, coarse speckled, fine speckled and cytoplasmatic. Then well-known model of transfer learning VGG-16 are train on MIVIA data set of HEP-type 2 cells. Data augmentation and data normalization used on pre-trained data to avoid over fitting because datasets of medical images are not very large. After the application of data augmentation and data normalization on pre-trained model, the performance of model is used to calculate by using a confusion matrix of VGG-16. VGG-16 achieves 84.375% accuracy. It is more suitable for the analysis of auto-immune diseases. Same as accuracy, we also use the other three parameters, Precision, F1 measures, and recall to check the performance of model. All four parameters use confusion matrix to find performance of model. The tools and languages also have great importance because it gives a simple and easy way of implementation to solve problems in image processing. For this purpose, python and colab is used to read and write the data because python provides fast execution of data and colab work as a simulator of python. The result shows that transfer learning is the most sufficient and enhanced technique for the analysis of auto-immune diseases since it provides high accuracy in less time and reduces the errors in image classification.

Keywords—Deep Convolutional Neural Network, indirect immune fluorescence, auto-immune diseases, Comparison analysis

I. INTRODUCTION

In the past few decades' immune fluorescence detection technology has been in the limelight due to its great importance in the field of medical health. It is a microscope based versatile and cost-effective technique. Indirect immunofluorescence detection technology (IIF) is mainly used for the analysis of the anti-nuclear antibody (ANA) autoimmune disease detection and treatment [1]. IIF is basically an imaging method and is used to detect the existence of the autoimmune diseases such as systemic autoimmune rheumatic diseases, dermatomyositis and primary biliary cirrhosis.

The IIF analysis is performed in three steps; the first step checks out the fluorescence signals (passing the light) through mitotic cell (body cells). The second step evaluates the intensity into three levels, i.e., negative, positive and intermediate, and the final step classifies both intermediate and positive patterns of the fluorescence and locates the auto antibody type.

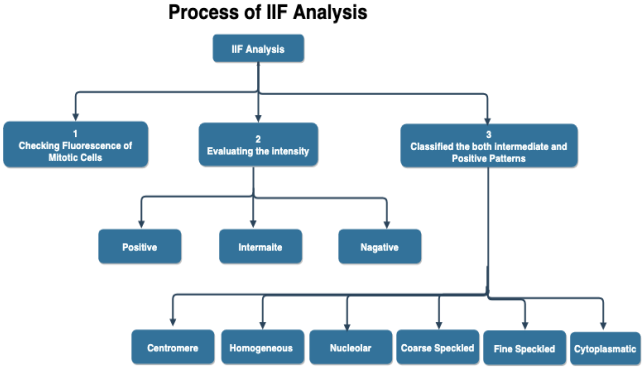


Figure I: Process Flow Chart of IIF Analysis

The staining pattern which is obtained as a result of the fluorescence signal (positive or intermediate) is classified into the six different classes.

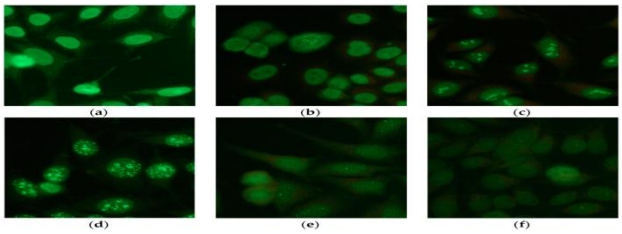


Figure II: Staining Patterns of HEp-2 Type 2 Cells

For large data the given method would become too long and time-consuming [2]. It's worthy to mention that in the medical field the computer-aided diagnostic system (CAD) is widely used to overcome all these limitations of (IIF) technology.

For a few years Deep Learning (DL) has been showing promising results and different real-world scenarios such as agriculture, industry, autonomous vehicles, smart cities and medical etc. DL techniques usually require a huge amount of data however, the availability of clean and domain specific data has always remained a tough challenge and the lack of availability of data catastrophically impacts the performance of DL model. The problems usually associated with lesser data are over fitting and inaccuracy of the trained model. In order to mitigate these problems, DL researchers

have developed several techniques such as data augmentation and image normalization. These techniques either leverage the knowledge of the existing model, or increase the data size in an artificial manner [3].

At the first instance, that will be trained different model of transfer learning on MIVIA data-set then applied data augmentation and image normalization on pre-trained model and check the accuracy to determine the performances of model. For instance, experiments, publicly available MIVIA dataset will be used. The database consists of (1457) images belonging to six (6) different classes, and for further classification different DL model will be used like VGG16. This model will be evaluated the performance transfer learning model effectively.

II. LITERATURE REVIEW

Huang *et al*., 2016 [4] explained textural features as well as statistical features analysis in a hybrid fashion for the classification process of image. Wiliem *et al*., 2016 [5] used method known as linear local distance coding for extraction of features and also utilized as an input for a linear SVM. In fact, jakob *et al*., [6] 2016 have used study for the combination of several features such as the morphological, global texture like the Rotation-Invariant Gabor features, also different kinds of LBP descriptors feature that were adopted for it to use able hybrid feature extraction method for the detection of cancer in tissues. M. Poostchi *et al*., 2018 [7] studied Various techniques, in which different algorithms were formed for division of objects over classes to decrease intra-class variance and increase inter-class variance based on their features, have been proposed to automatically localize area of lesion and to determine classified type of disease like malaria. Most of the proposed algorithms of classification follow the same basic steps; preprocessing, segmentation of images, feature extraction, and image classification. These all steps and processes that have been proposed for each one of them were described. Natalie Best *et al*., 2020 [8] studied mining images and analyzing the efficiency of transfer learning model. In which the images are analyzed by using image-based software artifacts and big data is not used in this research paper. Santa Di Cataldo *et al*., 2020 [9] proposed a classification approach based on Subclass Discriminant Analysis (SDA), a dimensionality reduction technique that provides an effective representation of the cells in the feature space, suitably coping with the high within-class variance typical of HEp-2 cell patterns. Abeer Badawi *et al*., 2021 [10] studied detection of COVID-19 by using chest X-Rays. In which several image processing techniques are used for X-rays analysis and different model of transfer learning like Dens Net 201, VGG-16, VGG-19 are used to study chest X-ray and then analyzed their performance measures. Gugan Kathiresan *et al*., 2021 [11] studied diseases of rice by using transfer learning technique in which three different model are compared without using GAN augmentation and the results showed bench mark performance of 98.3%

III. PROPOSED METHOD

This research paper proposed work in which MIVIA dataset has been taken from online resources. Then python language selects for experimental analysis and colab is used as a simulator for python language, whereas python is a high-level programming language and colab is a web-based application using for python. Python is an easy and simple language to work with limited code. The proposed method for auto immune diseases used deep learning approach for the analysis of auto immune diseases. MIVIA dataset trained on well-known model of transfer learning VGG-16. Apply data augmentation and image normalization on pre trained model then use parameters of confusion matrix to check the performance of model.

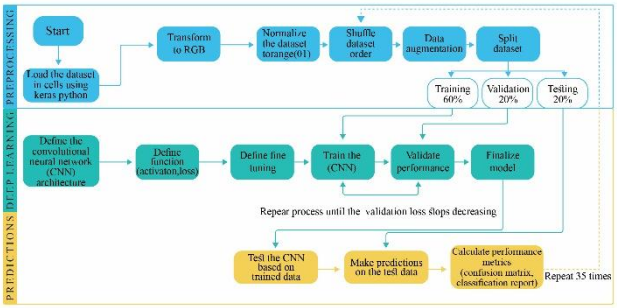


Figure III: Flow chart of proposed solution

A. *Data set*

MIVIA data set is publicly available it will be used publicly available MIVIA data set. The database consists of (1457) images belonging to six (6) different classes.

Table I. Characteristics of MIVIA Dataset

Characteristics	**MIVIA**
No Of Specimen Images	28
No Of Images	1457
No Of Classes	6
Classes Name	Homogeneous, Centromere, Cytoplasmatic, Nucleolar, Coarse Speckled and Fine Speckled.

B. *Tools and languages*

Python language is used in colab for proposed work. It provides single interface with limited human effort. In python language there are many libraries which have their own basic functions, like pandas which are used for data frame of CSV dataset. NumPy, while Matplotlib and seaborn is used for visualization of data. SK-learn is used for selection of model and keras library is used for deep

learning model so, all these libraries are used in research simulation.

C. *Transform to RGB*

In this step RGB will be converting our image data into grey scale. This will be help in training to consume less time with less memory and perform best model execution. It is color coding for black and white and the next step will be data normalization.

D. *Data Augmentation and normalization*

It is important to use all normalized features to avoid over fitting of values and convert the features in form of (0, 1) this is also known as label encoding. In this step the amount of data using data augmentation for training model. Its deep learning techniques which issues to create new training data based on existing data set.

E. Model Convolutional Neural Network (CNN)

Convolutional Neural Network is an algorithm of deep learning that absorbs input images and assigns different weights and deviations to many different objects in the image, to be able to distinguish each other. Compared with other classification algorithms, the pre-processing required in Conv Net is much lower. In the original method, the filters were designed by hand, after sufficient training; Conv Nets was able to learn these filters or features. The given below figure shows full structure of convolutional neural network (CNN).

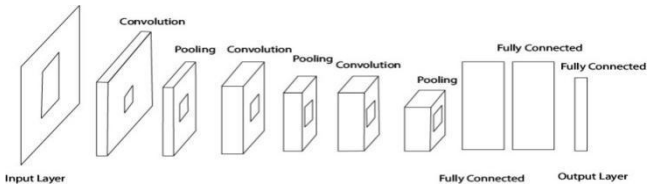


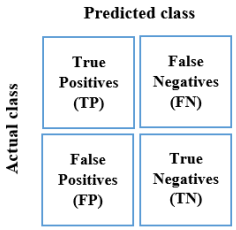
Figure IV: Convolutional Neural Networks (CNN)

In such research work we will be using model or version of CNN model. In given research VGG-16 model is used to train in transfer learning.

This is an advance deep learning model using for image processing. It is also working on deep neural network and all the above advance version of CNN model which already explained in introduction section [12].

F. *Performance Measure*

A very important step is to identify the performance of proposed model and calculate accuracy, precision, F1 measures and recall. That is how much of proposed model and how much proposed work results are accurate. In this step confusion matrix is used for calculating the performance of model. These performances identify by the accuracy, precision, recall, and F1 score of model.

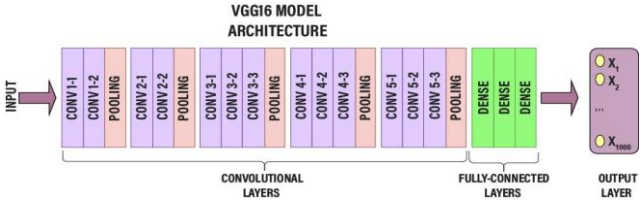


Measure	formula
Accuracy	(TP+TN)/(TP+FP+FN+TN)
Precision	TP/ (TP+FP)
Recall	TP/ (TP+FN)
F-Measure	2*Precision*Recall/ (Precision+Recall)

Figure V: Performance measures

G. *VGG-16*

VGG-16 is used to train convolutional neural network of Image Net dataset, it has a collection of 14 million images, which belongs to 22,000 different categories. VGG-16 achieved with high accuracy in training images of more significantly it is used to train millions of images. VGG model has 16 convolutional and max pooling layers and three dense layers for the fully connected layer of 1000 nodes.



IV. RESULTS

Proposed work represents all results are explaining and practical implementations about auto immune diseases prediction and classification are also mentioned. We used Deep Learning approach for human classification, and proposed solution also used convolutional neural network (CNN) classifier model for Prediction. In last the results are evaluated in the term of final accuracy. The below steps are used for proposed work [13].

A. *Data Normalization*

The scaling of features is a method which used for normalization of independent features in data for fixed range which is performed for data preprocessing. The two best ways used for feature scaling, standardization and normalization of images.

1. Standardization: it excludes your observations by means of all observations, initially columns are divided by using standard deviation then take own observations.

$$Xnew = \frac{Xi - Xmean}{\text{Standard Deviation}}$$

2. Normalization: For data normalization observation is subtracted from minimum of all observations and then divided it by maximum and minimum, feature will be scaled by this way.

$$Xnew = \frac{\text{Xi} - \min(\text{X})}{\max(\text{x}) - \min(\text{x})}$$

B. *Data Augmentation and Data Splitting*

It is used to improve the existing training data set by creating new data set, in which existing data set contains 873 images and covert these images to 6875 training set.

The table shows complete data splitting and data augmentation.

Table II. Data Augmentation and Data Splitting

Data Set	Training	Validation	Testing	Overall
Percentage of total dataset	60%	20%	20%	100%
Number of images	873	291	291	1455

Data Set	Training	Validation	Testing	Overall
Percentage of total dataset	60%	20%	20%	100%
Number of images	6875	291	291	7457

In above figure there are results are shown, data splitting shows 60% training, 20% validation, 20% testing and overall is 100% of our actual data set. After that the same procedure used for data augmentation, where actual data set become 6875.

C. *Model of transfer learning*

VGG-16 is a model which is used for transfer learning in proposed research.

a. *VGG-16*

VGG-16 is use for training of convolutional neural network of Image Net dataset it has a collection of 14 million images which belongs to 22,000 different categories. VGG-16 achieved high accuracy in training images but more significantly it is use to train millions of images. The below is our research confusion matrix of VGG-16 [14].

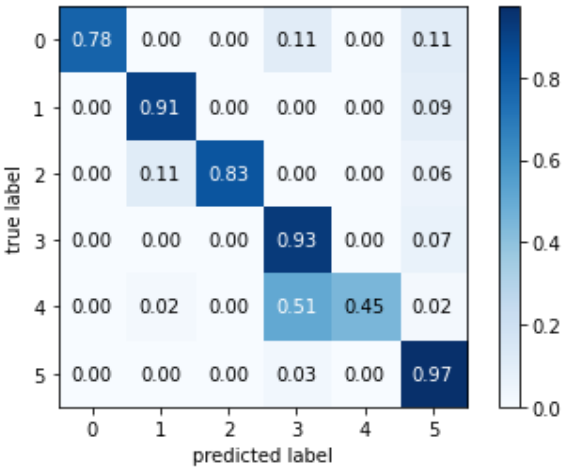


Figure VI: VGG16 Model Confusion Matrix

Confusion matrix represents total number of actual labels and predicted labels for classification.

The figure below showed VGG-16 model training and validation accuracy.

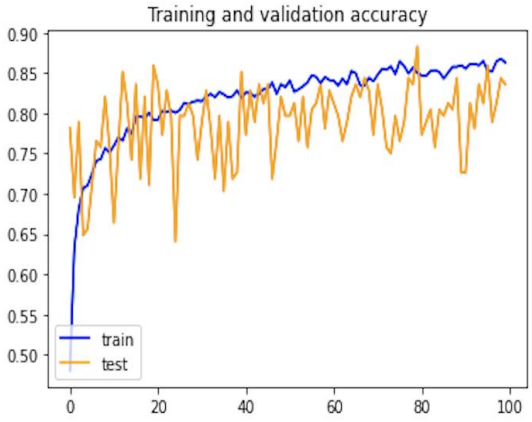


Figure VII: VGG-16 Model Train and Validation Accuracy

This figure shows difference between training and validation loss.

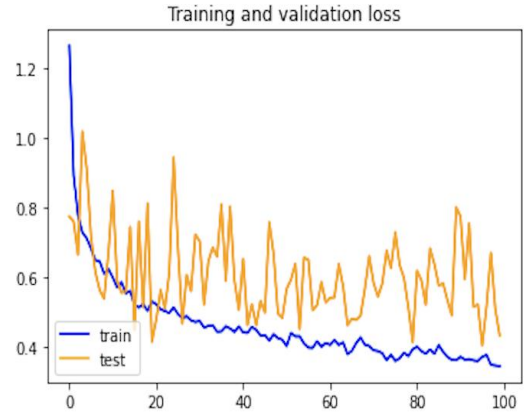


Figure VIII: VGG-16 Losses of Train and Validation Set

So, this figure shows all the losses of training and validation set which shows very low percentage as compare to validation of results training. The table shows score of proposed model in term of accuracy, precision, recall and f1-score.

Table III: VGG-16 Performance Measure

AC (%)	PR (%)	RE (%)	F1 (%)
81.88	85	81.16	79.5

In performance, the report showed that the precision (PR) is 85% and recall (RE) is 81.16% and the average accuracy (AC) of model is 81.88% which is good. The average accuracy represents the F1 79.5% score.

V. CONCLUSION AND FUTURE WORKS

paper proposed step by step methodology for auto immune disease prediction as well as use advanced deep learning model. Such work provides a sufficient and enhanced

technique for the medical's areas for the analysis of medical images. MIVIA data set which is taken from online resource Data set has been imported into these languages by using specific libraries, which is used for data reading and writing. Data augmentation technique is used to create new data on existing data for model. Data normalization, generate performance from confusion matrix from supervised algorithm. Deep learning is used to apply on algorithms of proposed model. The algorithms VGG-16 got 84.3785% accuracy for auto immune disease prediction. As well as, it is very sufficient and enhances techniques of deep learning for auto immune diseases prediction that provide a better decision for future scientist.

VI. Acknowledgement

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