PRIOR DETECTION OF ALZHEIMER'S DISEASE WITH THE AID OF MRI IMAGES AND DEEP NEURAL NETWORKS

Karthik S A[1*], PriyaNandihal[2], Seemanthini K[3],Manjunath D R [4], Liyakathunisa[5]

[1]Department of Information Science and Engineering, B M S Institute of Technology and Management, Bangalore, Karnataka, India

[2]Department of Computer Science and Design, Dayananda Sagar Academy of Technology and Management, Bangalore, Karnataka, India

[3]Department of Machine Learning, B M S College of Engineering, Bangalore, Karnataka, India

[4]Department of Computer Science and Engineering, B M S College of Engineering, Bangalore, Karnataka, India

[5]College of Computer Science & Engineering, Taibah University, Madinah, Saudi Arabia

Email: karthiksa1990@gmail.com[1*](corresponding author), talk2priya.nandihal@gmail.com[2]
seemanthinik.mel@bmsce.ac.in[3], manjunathdr.cse@bmsce.ac.in[4], lansari@taibahu.edu.sa[5]

DOI: https://doi.org/10.22452/mjcs.sp2022no2.2

ABSTRACT

Alzheimer's disease is a degenerative disease in which brain cells die and deteriorate. It is the most prevalent reason for dementia, which is defined as a progressive decrease in thinking, conduct, and social skills that impairs a person's capacity to operate independently. Although it is fatal the early diagnosis of Alzheimer's can be extremely helpful. Our main aim is to help with the diagnosis of this disease in its early stages using the VGG16 classifier which is a convolutional neural network (CNN) that is 16 layers deep. The dataset consists of MRI images of the brain. Data augmentation is done to significantly increase the diversity of data available and Data pre-processing helps to enhance the overall truthfulness of the proposed approach.

Keywords: Dementia, VGG16, CNN, Data Augmentation, Data Pre-Processing

1.0 INTRODUCTION

Alzheimer's disease is a chronic neurological illness that normally starts slowly and gets worse over time. The most common side effect of Alzheimer's disease is an inexorable decline in behavior and social dispositions that interfere with a person's daily routines. Affected individuals initially experience very minor loss of memory and uncertainty. This is referred to as chronic deterioration. However, as years progress; such ailments get even more acute. Individuals with this condition would be incapable to communicate with close relatives or unable to judge what's going on around them. Such illness is incurable. Healthcare professionals and caretakers have to concentrate on precise therapy in the postponement of memory loss and have to ensure that everyone involved has a decent quality of life.

Mild cognitive impairment (MCI) is a condition wherein a patient's intellectual development displays slight changes which people near the affected individual might notice. Experts have determined that individuals with MCI [1] have a greater chance of developing Alzheimer's disease than healthy individuals. MCI is much more common in the 60-80 year age group. Once initial complaints manifest, one can lead the life for up to the next 8 years. However, some folk's sickness progresses swiftly while others progress quietly. The reason for the disease is still unknown however possible reasons are genetic factors, geography, bad lifestyle, and general fitness all have a part to play. MCI is critical in preventing the progression of memory deterioration and enhancing individual happiness in Alzheimer's patients. The Alzheimer's disease Neuroimaging Initiative (ADNI) database provides MRI brain scans for analysis purposes. The deep neural network is a new machine learning technology that can perform a variety of classification functions. Over simple findings, the convolutional neural network is dominated by different image categorization functions. Data augmentation is one of the strategies used by CNN-based systems to improve picture classification performance in dataset layers with different weights. Among the many CNN-based deep neural networks constructed, researchers were able to get a significant result on the ImageNet Challenger, which is the most important image classification and segmentation challenge in the field of image analysis. In medical grading, the CNN-based deep neural system is commonly utilized. Since CNN is a strong feature extractor, using such a model one can successfully segment medical images which can save time and space also. As CNN is such a good feature extractor, using this one can categorize medical images with effective space and time complexity. Deep learning models face several obstacles, including over fitting, gradient shrinking, and diverse emergence of dopaminergic neurons. The VGG16 framework is used in this work. VGG16 layout is a convolutional neural network (CNN) in that there are sixteen layers with different weights. This is a huge group with around 138 million (approximately) features. The proposed work aims to focus on a recommendation system that assists healthcare professionals and patients so that future outcomes can be taken care of by looking at symptoms of Alzheimer's disease. Fig. 1 shows a normal MRI image and an MRI image of a person affected by Alzheimer's disease

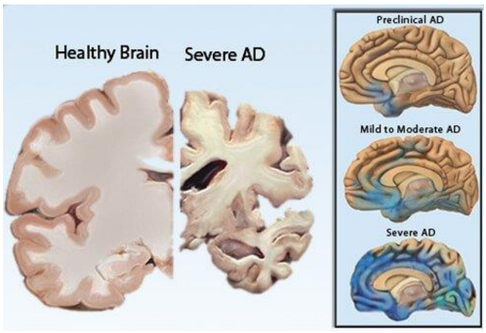

Fig.1: Normal vs. AD image and its appearance in different stages

The organization of the rest of the paper is as follows: In section 2, novel approaches for premature detection of Alzheimer's disease used in literature are described. In sections 3 and section 4, the convolutional neural network, the VGG16 model has been presented followed by a 3-way classification methodology to detect Alzheimer's disease has been presented. In section 4, an experimental result has been presented to prove the efficacy of the proposed research. Finally, a conclusion and future enhancement have been presented.

2.0 REVIEW OF RECENT WORK

In this piece of writing, a few of the popular methods of early detection of Alzheimer's Disease using MRI Data and Deep Neural Networks from the literature are discussed.

Islam et. al describe Alzheimer's disease-affected individuals exhibit memory loss, disorientation, speech difficulties, unable to comprehend and compose a few aspects [2]. The disease eventually, kills cells of the brain by destroying the prefrontal cortex which controls respiration and heart function. The author made the following main contributions; a deep convolutional neural network is capable of detecting Alzheimer's disease and classifying its present stage. Despite learning from a tiny dataset, the network outperforms other methods of diagnosing Alzheimer's disease. As a result, this author use using automated algorithms to detect early signs of Alzheimer's disease from such data. Gunawardena et. al explain that manually analyzing vast quantities of images to obtain the best accurate diagnosis is one of the significant challenges [3]. Hence, there is a huge demand for an automated method for diagnosing Alzheimer's disease with an enhanced version in terms of cost also. It adapts a classifier model to each patient using locally weighted learning and calculates the sequence of biomarkers. ADNI data are used to compare AD patients and MCI patients. As a result, the author advises using automated algorithms for the pre-detection of AD symptoms using such data.

Ahmed et. al describe the structure of a neural network as six layers in total [4]. A Convolutional layer is an initial layer. which is used to produce extracted features, a filter is passed over the input images in this layer. After that, a reduction process is performed using a pooling layer. Thereafter, a fully connected layer is used. Only two neurons in the output layer indicate whether or not there is Alzheimer's disease. The activation function RELU was chosen for two convolutions and the fully connected layer. The neural network was optimized using the stochastic optimization function Adam Optimizer with a learning rate of 0.001. And, using cross-validation, the data were randomly divided into train test data. The neural network's performance was significantly improved thereafter. Sarraf et. al describe one architecture that is built on the explicit premise that raw data is made up of 2-D images. Small sections of the image are used as inputs to the hierarchical structure's outermost layers [5]. It has a Convolution layer as well as additional network topologies such as a Pooling Layer, Normalization Layer, and Fully-Connected Layer. In CNN architecture, the Convolutional Layer is very significant.

Fuse et. all describes the use of magnetic resonance imaging (MRI) in the diagnosis of Alzheimer's disease (AD) [6]. Grey matter and hippocampus volumes in patients with Alzheimer's disease are smaller than in healthy people, as per previous research. Minor fluctuations in image registration and cross-sections of sliced images have a major effect on volume, making it more challenging to assess regional brain volume. Positions of all AD and HS data should be matched for image comparison between individuals. Escudero et. al describes that machine learning technologies aid in the elucidation of data for medical conclusions and verdicts [7]. However, most current machine learning systems fall short of simulating the individualized diagnostic process in clinical settings. The clinician determines which tests are most appropriate for each patient in practice. As a result, innovative techniques for assisting doctors are desirable in more productive (in terms of the number of tests and/or cost) and tailored disease identification. Billones et. al describes. pooling which reduces the magnitude of the data while also, in fact, summarizing the results of adjacent groupings of inputs [8]. The Dropout layer is mostly used to reduce the number of tests. N. A. Mathew describes a novel way of detecting Alzheimer's disease using a 3D MRI picture [9]. When a picture is first chosen, it is normalized so that it may be aligned into a single coordinate system. The Grey Level Co-Occurrence Matrix (GLCM) technique is used to calculate statistical properties like contrast, correlation, homogeneity, and entropy. The decisive feature in this study is hippocampus atrophy. According to findings, the hippocampus volume in early Alzheimer's sufferers was only 13.9 per cent which is lower than in healthy individuals.

X. Song et. al describe a procedure that uses a mixed elevated system and graphing modelling technique (GMT) [10]. The model is constructed using a mixed elevated system that spans stable, dynamic, and data on approximately, whereas GMT is utilized to increase classifier efficacy. The proposed system performs well in experiments using the (ADNI) dataset. Ahmed et. al have given a complete study of robotic dementia diagnosis methodologies employing clinical imaging techniques and ML techniques [11]. Researchers discovered that, although numerous scholars focused on Alzheimer's disease, new research proves decent performance in identifying different dementias, which continues a key concern. Deep learning techniques to advanced imaging analytics have shown promise in the detection of different other kinds of dementia. V. Jain et. al provided a unique DBAC model strategy for identifying and categorizing dementia among separate types relying upon the predominance and seriousness of dementia in the current MRI data [12]. The presented method has a 74 per cent average accuracy in predicting MCI and therefore can categorize dementia into four groups based on its predominance in MRI data. Kam et. al propose a new CNN architecture for learning embedding characteristics using BFNs has been conveyed [13]. Depending on the large-scale and high voxel-wises patio temporal patterns of the resting-state brain operational connectors, this research illustrates the efficiency of deep learning in Alzheimer's detection. Guo et. al explain an extended deep learning approach and statistically relevant textual data offered in the work for the timely identification of Alzheimer's disease [14]. The study looks somewhere at the benefits of better deep learning models for identifying frequent events in healthcare, and how they can cause premature Alzheimer's disease diagnosis.

The research presented here shows that hippocampus degeneration is a good early indication of Alzheimer's disease. The below facts reveal the comparative analysis in the present context of the article.

Authors	DataSet	Method	Accuracy
Albright et al., 2019	ADNI	Neural network model	86.60%
Alickovic & Subasi, et al., 2020	ADNI	Random forest	85.77%
		K- Nearest Neighbours	84.27%
		Naïve Bayes	75.16%
		Artificial Neural Network	76.03%
		Support Vector Machine	83.15%
Shahbaz et al., 2019	ADNI	Decision Tree	74.22%
		Generalized Linear Model	88.23%
		Deep Learning	78.32%
Islam & Zhang, 2018	OASIS	Deep Convolutional Neural Network	93.12%

Table 1: Comparative analysis of different methods

From the review of the literature, one can understand AD is regarded to be the most frequent cause of dementia, with just one out of every four persons diagnosed with the condition at the appropriate time. Cognitive, and emotional examinations as well. Hence there is a great scope for better diagnostic tools. Many new emerging machine learning algorithms can be used to successfully produce such tools, which aim to improve the accuracy of AD forecasts so that the treatment given to the patient is effective.

3.0 METHOD

In the existing system, one can see that the classification of AD is binary, where one has to determine if it is Alzheimer's disease or not. In our proposed system, our objective is to achieve a three-way categorization of Alzheimer's disease from MRI using VGG16 architecture [10]. Specially we propose to classify patients into Alzheimer's in its three stages that are Mildly Demented, Very Mild Demented and Non Demented. Magnetic resonance imaging (MRI) is a non-invasive neuro imaging technique that can be used to study the neural correlates of complex cognitive processes, such as learning and memory. Using VGG-16, a convolutional neural network architecture that has 16 layers, we can create a model to detect if the patient has Alzheimer's or not. Layers used in the proposed approach are Convolutional layers, Max Pooling layers, Activation layers, Fully connected layers

3.1 The Convolution Neural Network (CNN)

The Convolution Neural Network (CNN) is a key concept in Deep Learning that is used to identify images. CNN stands for Convolutional Neural Network. It is a form of a Feed-forward Neural Network. The layers and schema employed in CNN are depicted in the diagram below. For extracting features, the Convolution and Max-pooling layers are used. In the end, classification is done using the fully connected layer.

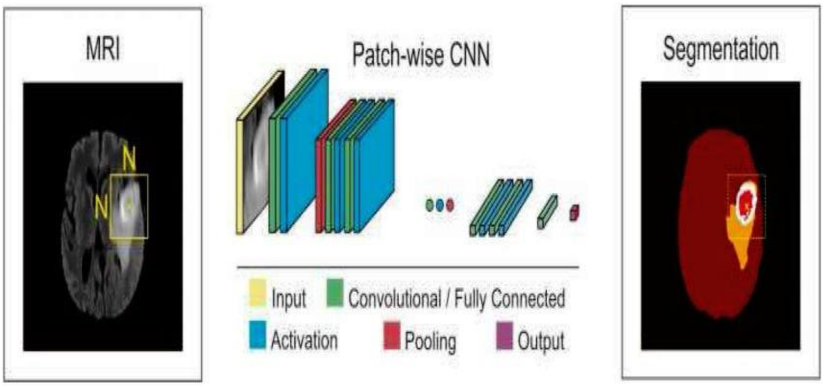

Fig. 2: Schema of a typical CNN

The layers Conv, Pool, and Dense of CNN are given input in diagram 1 above. These layers provide the function of a feature extractor. The output layer serves as a classifier, determining if the image depicts a convolution or normal. The following are the steps involved in constructing a convolutional neural network:

- Split the dataset into training and testing sets after loading it.
- reshape the dataset to the model's specifications
- Create a CNN model in sequential order by layering the layers one by one.
- Create the model's layers: Conv3D's first layer (Input Layer) deals with the input clips.
- A pooling layer is used in the second layer (Hidden Layer) to reduce the number of parameters and computations in the network. Every node in the first layer is connected to every node in the following tier using fully connected layers. Flatten is utilized to create a link between the Conv3D and Dense layers.
- The third layer (Output Layer) - In Neural networks, the output layer is known as the dense layer
    a. Use the optimizer and loss function to compile the model, and the accuracy metric to calculate the accuracy score.
    b. Use the fit function to train the model.
    c. On a new dataset, the Predict function is used. To determine whether the model is right, compare the anticipated value to the actual outcome.

4.0 VGG16 MODEL

The VGG16 model and layers are depicted in Fig. 2 and 3 which include 16 weighted layers[12,13,14]. With this step, it takes to focus on getting 3x3 filter convolution. layers and always using the same .padding of the 2×2 filter and the maxpool layer with the Stride 2. All through the architecture, the mentioned layers are ordered similarly. Finally, it has two CC and a SoftMax for output.

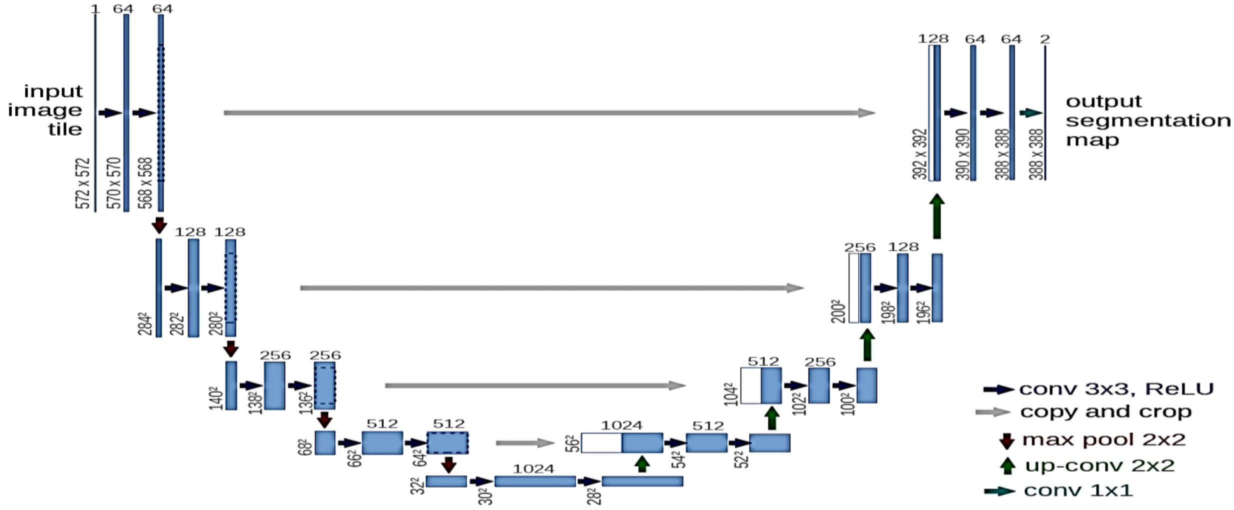

Fig. 3: VGG16 Architecture

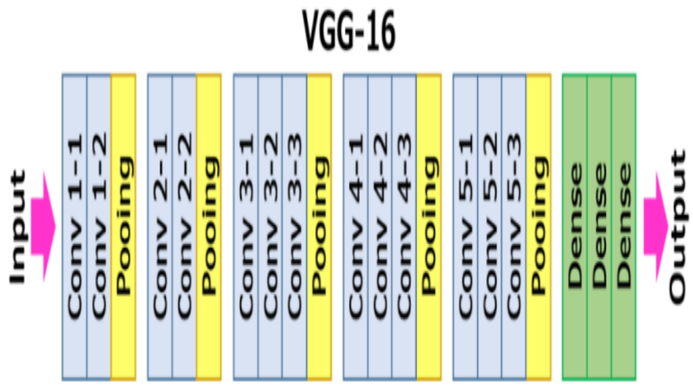

Fig. 4: Layers in VGG16

The feed to the conv1 layer is a 224 x 224 color picture with a fixed size. The image is sent to the sequence of convolutional (Conv.) layers, with the filters set at a 3×3 receptive field. Also, it uses a 1×1 convolution filter in one of the setups, which is a linear transformation of the input channels. The convolution stride is set to 1 picture element and fills the space of the transformation. Layer input is set to 1 pixel for 3×3 transformation. layers so that spatial resolution is preserved after convolution. Five coats max as part of the conversions class to perform spatial pooling. After a series of convolutional layers, three Completely Connected (CC) layers are added [15]: the first two layers each have 4096 channels, and the third performs 1000 ILSVRC classifications, so there are 1000 channels (one for each category). Softmax shift is the last shift. The fully connected level is configured in the same way in all networks. The activation function used in this work are ReLu and Softmax. If the input is less than 0, the output of the rectified linear unit is 0, if not it is the original output. On the other hand, if the input is larger than 0, the output will be the same as the input

$$f(x) = \max(x, 0) \quad (1)$$

5.0 METHODOLOGY

In this section system, the architecture for early detection of Alzheimer's disease has been presented. The proposed architecture has 3 phases such as data augmentation, model training and classification. The proposed system architecture works with MRI images. The OASIS dataset contains data on patients with Alzheimer's disease and includes 502 features for 1813 individuals in the database used in this study. Because this contains information from several sessions per person, this database is long. The dataset contains several metrics (also known as features) that would be used to diagnose Alzheimer's disease: Rank on the Mini-Mental State Examination (MMSE) age, gender, frequency of consultations, and so on. Just like previously stated, the MMSE value is the primary criterion for diagnosing Alzheimer's disease. In reality, if such an individual has Alzheimer's disease, the MMSE level drops on just a regular basis. When a data set has been preprocessed, the data augmentation phase is passed to train a major neural network is used. Finally, classification is done. Fig. 4 and fig. 5 describe the proposed system architecture and entire methodology (Flow).

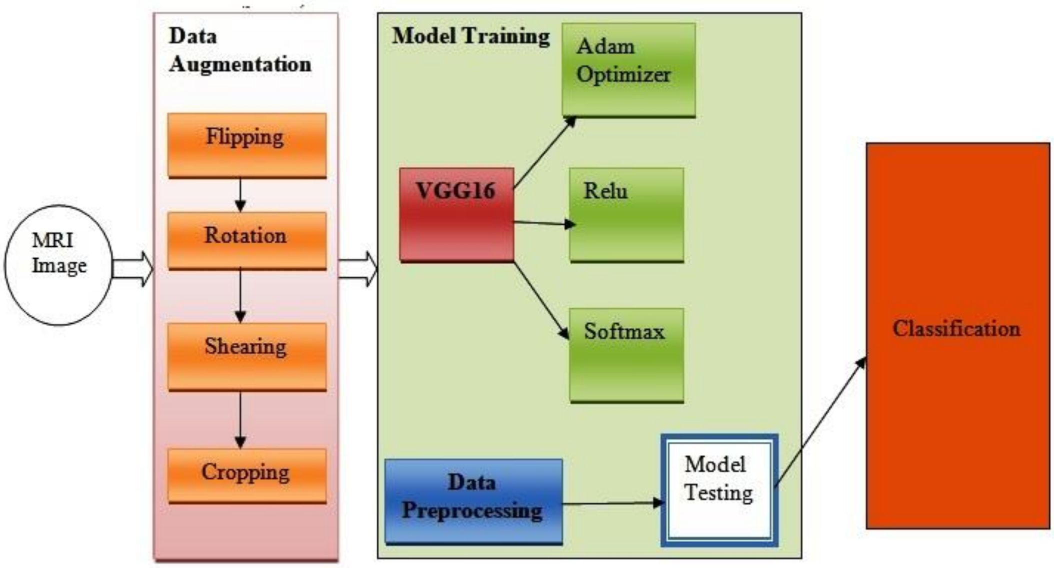

Fig. 5: System Architecture

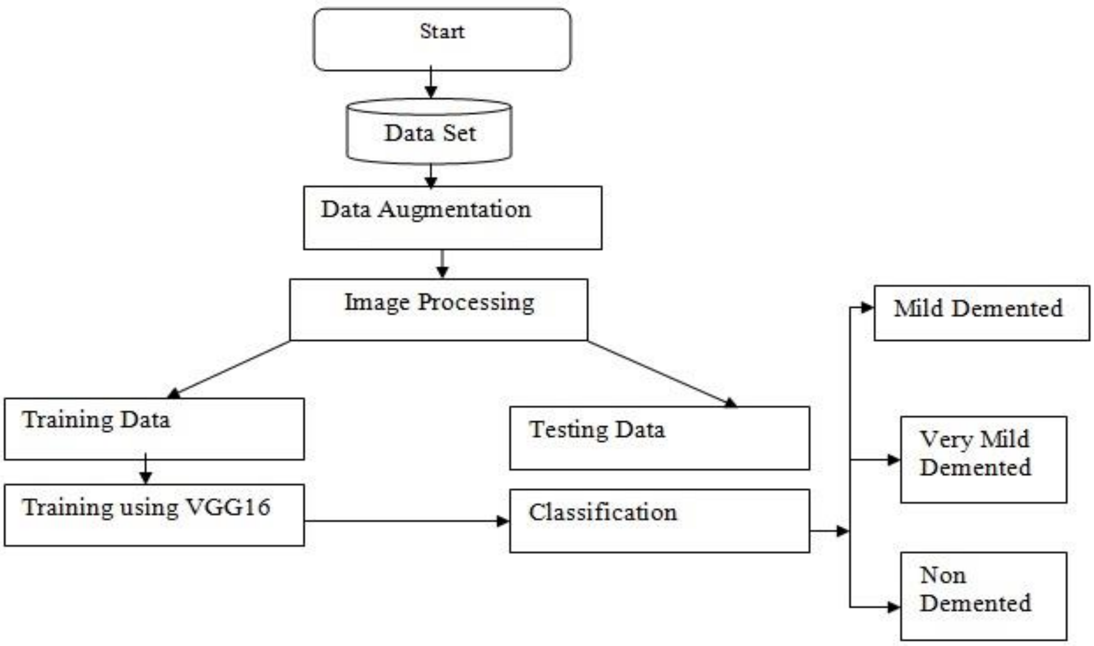

Fig. 6: Flow of proposed approach

The above Fig. 6 clearly shows the data flow of the proposed system architecture where data is collected from the OASIS database then it is augmented to test with a variety of data. Before feeding to the projected model one has to take care of MRI image quality by undergoing image processing activities. Data is trained and tested separately to classify the disease as mild, very mild or moderate. The use case diagram of the proposed methodology is also given in
Fig. 7.

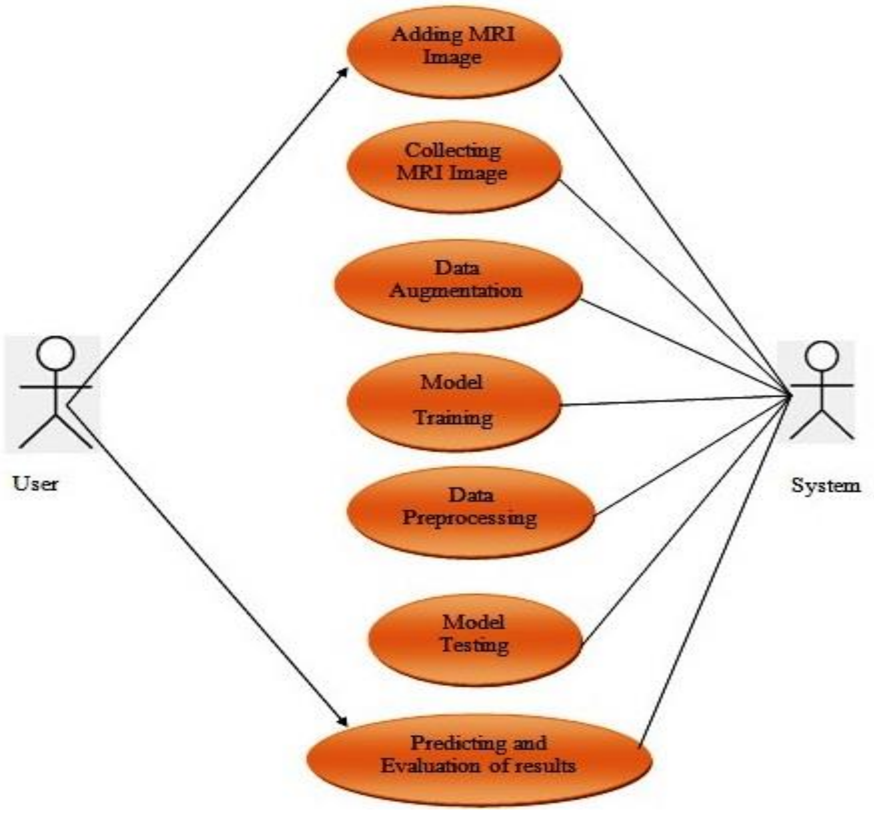

Fig. 7: Use case diagram of proposed system architecture

6.0 DATA AUGMENTATION

Data expansion is a way to allow experts to enhance substantially the variety of information accessible for training without truly collecting supplementary facts. Increases in data [16] are widely employed in training vast neuronal networks. In deep training users require vast volumes of information and, in some circumstances, hundreds of millions of images can't be collected, which means that increased data is rescued. It helps us enhance the data set size and introduce data set variability. Rotation, shearing, zooming, cuts, flipping, and luminous levels are the most widely employed procedures. Images after data augmentation are shown in Fig. 8.

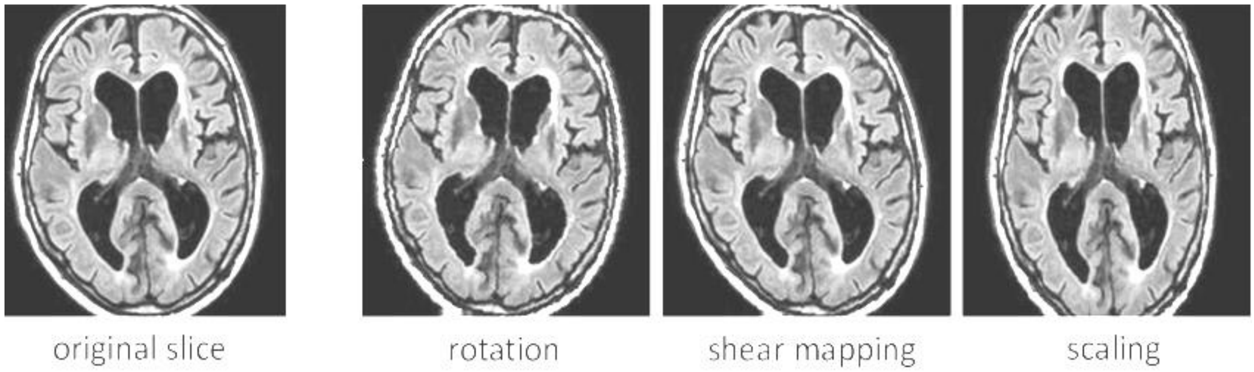

Fig. 8: Augmented Data Images [25]

6.1 Model Training

The VGG-16 training model is depicted in fig. 9 which [17] is a pertained network that can categorize images into 1,000 kinds of objects. The network has so learned rich depictions for a wide range of images. About 60% of the data collected has been fed for training the image.40% of the image is for testing. The accuracy of the training data is mentioned in section 5.

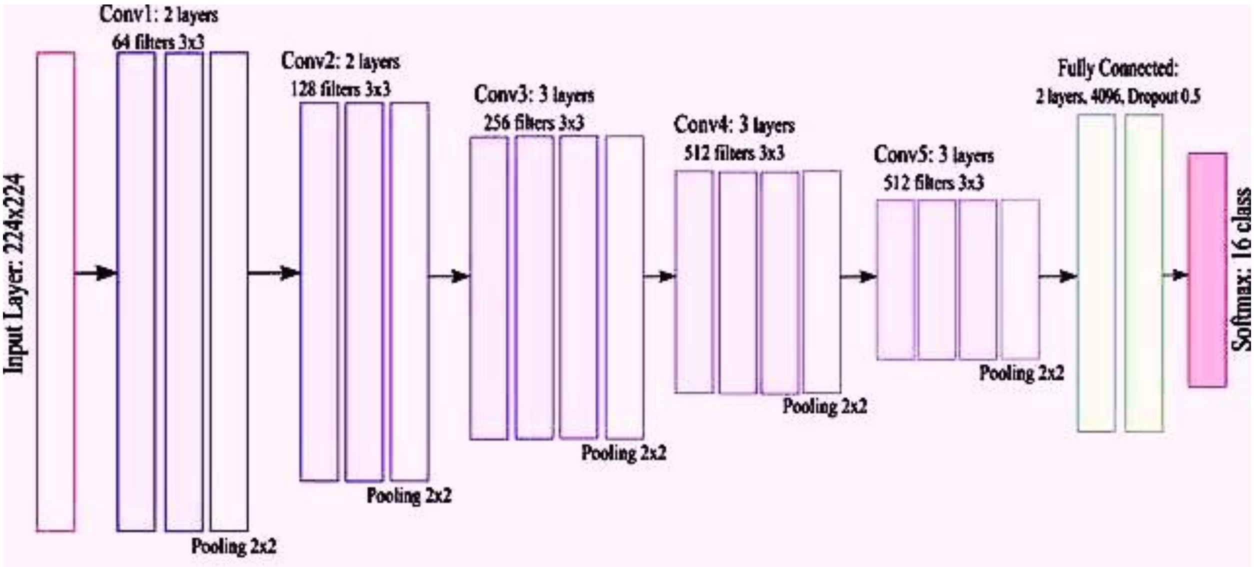

Fig.9: Model Training Using VGG16

6.2 Data Preprocessing

Pre-processing data is a crucial stage in the context of data quality and vital information which may be acquired directly, influences the model's ability to learn and it is therefore of paramount importance that we pre-process our data before inserting it into the model. Pre-processing approach used here is edge mapping parameterization. In edge, matching is parameterized in the sense that everything tries to capture the background color by describing it as a parameterized shape and adapting a 2D image to it. The prerequisite for the said approach is no considerable brightness fluctuation for a particular tissue type. The outcome of the approach is a background-corrected image. MRI images after pre-processing are displayed in fig. 10. This means that when data is obtained from various sources [18], it is collected in various formats which cannot be analyzed. This phase is necessary since actual data often contains noises, lacks values and may not be used for learning models and to achieve better outcomes. It may not be used in an unsuitable format.

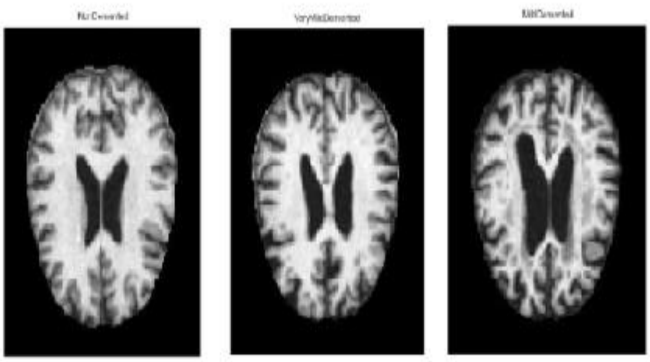

Fig. 10: Processed MRI Images

6.3 Model Testing

The model is tested [20] once the test data have been pre-processed. This is done to improve the overall model correctness. Models that have not been trained must be tested on data by considering the remaining 40% of the data.

7.0 PERFORMANCE METRICS USED

After implementing the VGG-16 Model on the data images, We were successfully able to classify the MRI Images [22,23] present in the dataset into the following three classes. The three classes classification primarily includes the following: Non – Demented, Very Mild –Demented, Mild Demented. fig. 11 shows the obtained images after classification.

(a) (b) (c)

Fig. 11: Different MRI Images presenting different AD Stages (a) Non-demented; (b)Very Mild Demented; (c) Mild Demented

To calculate the accuracy of the proposed results we used the following equations. Obtained values are shown in table 2. A comparison of the proposed approach with existing methodologies is shown in fig. 12.

$$\text{Accuracy} = \frac{TN+TP}{(TN+TP+FP+FN)} \quad (2)$$

$$\text{Recall} = \frac{TP}{(TP+FN)} \quad (3)$$

$$\text{Precision} = \frac{TP}{(TP+FP)} \quad (4)$$

Table 2: Comparison of the proposed approach with the existing approach

Method	Accuracy	Precision	Recall
Chaddad et al. (2018	0.812	0.9137	0.8599
Li et al. (2019)	0.8339	0.8807	0.8567
Kim et al. (2019)	0.8507	0.8489	0.8498
Proposed	0.9162	0.9278	0.9172

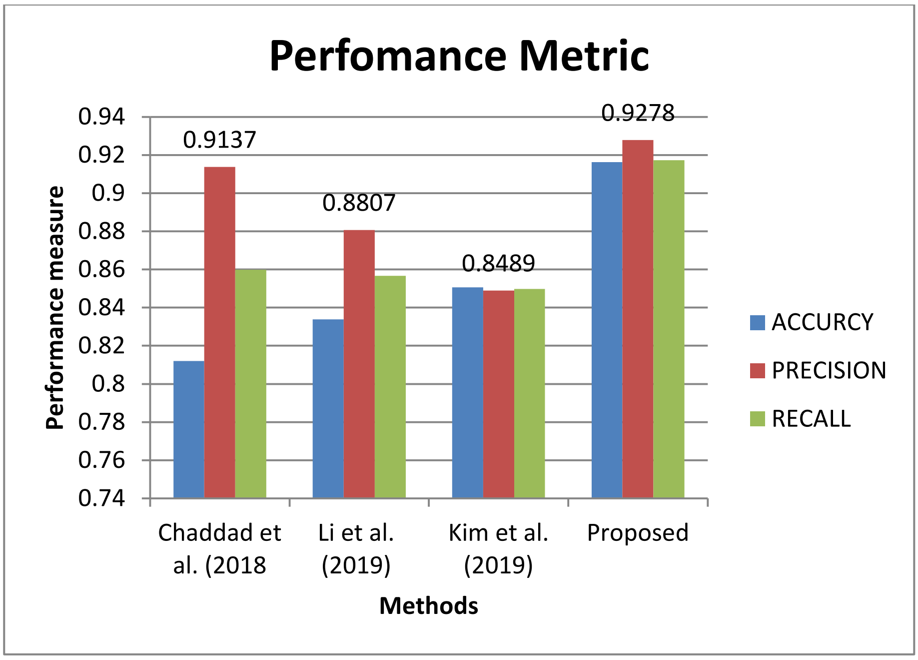

Fig. 12: Comparison of the proposed approach with the existing approach

True label \ Predicted Label	Mild Demented	Non Demented	Very Mild Demented
Mild Demented	79	14	11
Non Demented	41	411	84
Very Mild Demented	23	87	263

Fig. 13: Confusion Matrix

Fig. 12 and 13 convey accuracy [24] and confusion matrix [25] respectively. From the diagram given above, one can judge that accuracy of about 92% on the training dataset and accuracy [26] of about 80% on the test dataset.
Since the aim of the article is a recommendation system testing of the application is done.

6.0 DISCUSSION

The main objective of this work is to help with the diagnosis of this disease in its early stages using the VGG16 classifier which is a convolutional neural network (CNN) that is 16 layers deep [27]. Since there is no cure for this disease, prior detection is only the best way to stop spreading to other cells. Hence a prompt effort has been made to develop a recommendation system for the prior detection of AD. In this system patients or health care professionals have to upload the MRI scan report to the proposed system, so that stages of Alzheimer's disease can be identified at the earliest. From the extensive experimentation results, which are depicted in Table 2 [28,29,30], one can conclude that the accuracy has been improved by almost 7% of the previous approaches. Precision is a prognostic factor, while recall is a quantitative indicator. The highest precision produces more effective findings than unnecessary ones [31,32,33], while the highest recall delivers the majority of significant findings. The reason for the improvement of results counters the existing approach quality testing has been done at every stage of system development. An obtained framework of results is depicted in Fig. 14.

Test Case Number	UTC-1	UTC-2	UTC-3	UTC-2
Test Case Name	DATA AUGMENTATION	MODEL TRAINING	DATA PREPROCESSING	MODEL TESTING
Sample Input	Brain MRI images	MRI images with increased variation	Brain MRI Images	Pre-processed Brain MRI images
Expected Output	Modified version of the dataset	Trained dataset	Images after noise reduction	Test dataset
Actual Output	Modification of the orientation of the dataset by rotating, zooming etc.	Dataset trained on 5121 images	Better quality image	Dataset tested on 1013images
Remarks	PASS	PASS	PASS	PASS

Fig. 14: Testing results

To assess the performance of the proposed approach a few databases are considered: Minimal Interval Resonance Imaging In Alzheimer's Disease (MIRIAD), Trajectory-Related Early Alzheimer's Database (TREAD), Alzheimer Disease Neuroimaging, Initiative (ADNI), Open Access Series Of Imaging Studies (OASIS). The below table depicts the efficiency of the approach with a different database. The reason for the drastic improvement in the OASIS dataset is more data dimensions are available, and efficient data pre-processing is done in early-stage classification by the presented approach. Table 3 depicts the accuracy of different data sets.

Table 3: Performance comparisons with different database

DataSet	Accuracy
ADNI	86.60%
MIRIAD	84.23%
TREAD	89.47%
OASIS	91.12%

7.0 CONCLUSION AND FUTURE SCOPE

The proposed system deals with the detection of Alzheimer's in its three stages: Mildly Demented, Very Mild Demented and Non-Demented using MRI images of the brain. Based on the correlation of the MRIs, the functional brain networks were used to train the neural network as coefficient correlation data. In comparison with existing methods, the suggested method for classifying dementia in three stages is a powerful tool for the premature recommendation of neurological illnesses. Experimental results and comparisons in the database of structural MRI scans show that the suggested technique has promising diagnostic outcomes for AD and mild cognitive impairment. For future development, one has to strengthen the proposed model through the deeper AD classification following its discovery in several stages, such as early, middle, and late-stage of Alzheimer's. Potential future work focuses on other mental illnesses, which are useful in the field of medicine. By using a methodology with higher precision, the overall accuracy of the model will be improved for bigger health datasets that supply supplementary facts.

REFERENCES

[1] R. Ju, C. Hu, p. zhou and Q. Li, "Early Diagnosis of Alzheimer's Disease Based on Resting-State Brain Networks and Deep Learning," in *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, vol. 16, no. 1, pp. 244-257, 1 Jan.-Feb. 2019, doi: 10.1109/TCBB.2017.2776910.

[2] J. Islam and Y. Zhang, "Early Diagnosis of Alzheimer's Disease: A Neuroimaging Study with Deep Learning Architectures", in *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, 2018, pp. 1962-19622, doi: 10.1109/CVPRW.2018.00247.

[3] K. A. N. N. P. Gunawardena, R. N. Rajapakse, N. D. Kodikara and I. U. K. Mudalige, "Moving from detection to pre-detection of Alzheimer's Disease from MRI data", in *2016 Sixteenth International Conference on Advances in ICT for Emerging Regions (ICTer)*, 2016, pp. 324-324, doi: 10.1109/ICTER.2016.7829940.

[4] S. T. Ahmed and S. Sankar, "Investigative protocol design of layer optimized image compression in telemedicine environment". *Procedia Computer Science*, vol. 167, pp. 2617-2622, 2020, doi: 10.1016/j.procs.2020.03.323.

[5] S. Sarraf and G. Tofighi, "Deep learning-based pipeline to recognize Alzheimer's disease using fMRI data", in *2016 Future Technologies Conference (FTC)*, 2016, pp. 816-820, doi: 10.1109/FTC.2016.7821697.

[6] H. Fuse, K. Oishi, N. Maikusa, T. Fukami and J. A. D. N. Initiative, "Detection of Alzheimer's Disease with Shape Analysis of MRI Images", in *2018 Joint 10th International Conference on Soft Computing and Intelligent Systems (SCIS) and 19th International Symposium on Advanced Intelligent Systems (ISIS)*, 2018, pp. 1031-1034, doi: 10.1109/SCIS-ISIS.2018.00171.

[7] J. Escudero, E. Ifeachor, J. P. Zajicek, C. Green, J. Shearer and S. Pearson, "Machine Learning-Based Method for Personalized and Cost-Effective Detection of Alzheimer's Disease", *IEEE Transactions on Biomedical Engineering*, vol. 60, no. 1, pp. 164-168, Jan. 2013, doi: 10.1109/TBME.2012.2212278.

[8] C. D. Billones, O. J. L. D. Demetria, D. E. D. Hostallero and P. C. Naval, "DemNet: A Convolutional Neural Network for the detection of Alzheimer's Disease and Mild Cognitive Impairment," *2016 IEEE Region 10 Conference (TENCON)*, 2016, pp. 3724-3727, doi: 10.1109/TENCON.2016.7848755.

[9] S. T. Ahmed and K. K. Patil, "An investigative study on motifs extracted features on real time big-data signals," *2016 International Conference on Emerging Technological Trends (ICETT)*, 2016, pp. 1-4, doi: 10.1109/ICETT.2016.7873721.

[10] X. Song, A. Elazab and Y. Zhang, "Classification of Mild Cognitive Impairment Based on a Combined High-Order Network and Graph Convolutional Network," in *IEEE Access*, vol. 8, pp. 42816-42827, 2020, doi: 10.1109/ACCESS.2020.2974997.

[11] M. R. Ahmed, Y. Zhang, Z. Feng, B. Lo, O. T. Inan and H. Liao, "Neuroimaging and Machine Learning for Dementia Diagnosis: Recent Advancements and Future Prospects", in *IEEE Reviews in Biomedical Engineering*, vol. 12, pp. 19-33, 2019, doi: 10.1109/RBME.2018.2886237.

[12] V. Jain, O. Nankar, D. J. Jerrish, S. Gite, S. Patil and K. Kotecha, "A Novel AI-Based System for Detection and Severity Prediction of Dementia Using MRI", in *IEEE Access*, vol. 9, pp. 154324-154346, 2021, doi: 10.1109/ACCESS.2021.3127394.

[13] T. -E. Kam, H. Zhang, Z. Jiao and D. Shen, "Deep Learning of Static and Dynamic Brain Functional Networks for Early MCI Detection", *IEEE Transactions on Medical Imaging*, vol. 39, no. 2, pp. 478-487, Feb. 2020, doi: 10.1109/TMI.2019.2928790.

[14] H. Guo and Y. Zhang, "Resting State fMRI and Improved Deep Learning Algorithm for Earlier Detection of Alzheimer's Disease", in *IEEE Access*, vol. 8, pp. 115383-115392, 2020, doi: 10.1109/ACCESS.2020.3003424.

[15] N. Mwamsojo, F. Lehmann, M. A. El-Yacoubi, K. Merghem, Y. Frignac, B. –E. Benkelfat and A. –S. Rigaud, "Reservoir Computing for Early Stage Alzheimer's Disease Detection", in *IEEE Access*, vol. 10, 2022 pp. 59821-59831, 2022, doi: 10.1109/ACCESS.2022.3180045.

[16] Abhijnashree, K. Chandana, R. Mariam, S. Mahadev and S. A. Karthik, "A Survey on Early Diagnosis of Alzheimer's Disease using fMRI Data and Neural Networks", in *Test engineering and management*, Vol. 83, 2020, pp. 4150-4155.

[17] N. M. Khan, N. Abraham, and M. Hon, "Transfer Learning With Intelligent Training Data Selection for Prediction of Alzheimer's Disease", *IEEE Access*, 7, 2019, pp. 72726-72735, doi: 10.1109/ACCESS.2019.2920448.

[18] V. Sathiyamoorthia, A. K. Ilavarasi, K.Murugeswari, S. T. Ahmed, B. A. Devi and M. Kalipindi, "A deep convolutional neural network based computer aided diagnosis system for the prediction of Alzheimer's disease in MRI images", *Measurement*, vol. 171, 2021, pp. 108838, doi: 10.1016/j.measurement.2020.108838.

[19] L. Yue, X. Gong, J. Li, H. Ji, M. Li and A. K. Nandi, "Hierarchical Feature Extraction for Early Alzheimer's Disease Diagnosis", in *IEEE Access*, vol. 7, pp. 93752-93760, 2019, doi: 10.1109/ACCESS.2019.2926288.

[20] M. Amin-Naji, H. Mahdavinataj and A. Aghagolzadeh, "Alzheimer's disease diagnosis from structural MRI using Siamese convolutional neural network", *2019 4th International Conference on Pattern Recognition and Image Analysis (IPRIA)*, 2019, pp. 75-79, doi: 10.1109/PRIA.2019.8786031.

[21] H. Fuse, K. Oishi, N. Maikusa, T. Fukami and J. A. D. N. Initiative, "Detection of Alzheimer's Disease with Shape Analysis of MRI Images", *2018 Joint 10th International Conference on Soft Computing and Intelligent Systems (SCIS) and 19th International Symposium on Advanced Intelligent Systems (ISIS)*, 2018, pp. 1031-1034, doi: 10.1109/SCIS-ISIS.2018.00171.

[22] E. Jabason, M. O. Ahmad and M. N. S. Swamy, "Classification of Alzheimer's Disease from MRI Data Using an Ensemble of Hybrid Deep Convolutional Neural Networks", *2019 IEEE 62nd International Midwest Symposium on Circuits and Systems (MWSCAS)*, 2019, pp. 481-484, doi: 10.1109/MWSCAS.2019.8884939.

[23] R. Cui and M. Liu, "Hippocampus Analysis by Combination of 3-D DenseNet and Shapes for Alzheimer's Disease Diagnosis", in *IEEE Journal of Biomedical and Health Informatics*, vol. 23, no. 5, pp. 2099-2107, Sept. 2019, doi: 10.1109/JBHI.2018.2882392.

[24] E. Hosseini-Asl, R. Keynton and A. El-Baz, "Alzheimer's disease diagnostics by adaptation of 3D convolutional network", *2016 IEEE International Conference on Image Processing (ICIP)*, 2016, pp. 126-130, doi: 10.1109/ICIP.2016.7532332.

[25] F. Li, L. Tran, K. -H. Thung, S. Ji, D. Shen and J. Li, "A Robust Deep Model for Improved Classification of AD/MCI Patients", in *IEEE Journal of Biomedical and Health Informatics*, vol. 19, no. 5, Sept. 2015, pp. 1610-1616, doi: 10.1109/JBHI.2015.2429556.

[26] S. A. Karthik and S. S. Manjunath, "Automatic gridding of noisy microarray images based on coefficient of variation", *Informatics in Medicine Unlocked*, 2019, 17, 100264, doi: 10.1016/j.imu.2019.100264.

[27] S. A. Karthik and S. S. Manjunath, "Microarray spot partitioning by autonomously organising maps through contour model", *International Journal of Electrical and Computer Engineering (IJECE),* 2020, Vol. 10. No. 1, pp. 746-758, doi: 10.11591/ijece.v10i1.pp746-756

[28] S. A. Karthik, S. S. Manjunath, D. P. Prakyath, S. Prashanth, K. Vamshi and Siddartha, "A Review on Gridding Techniques of Microarray Images", *2019 1st International Conference on Advanced Technologies in Intelligent Control, Environment, Computing & Communication Engineering (ICATIECE)*, 2019, pp. 64-67, doi: 10.1109/ICATIECE45860.2019.9063822.

[29] S. A. Karthik and S. S. Manjunath,"An Enhanced Approach for Spot Segmentation of Microarray Images. Procedia Computer Science", vol. 132, 2018, pp. 226–235, doi: 10.1016/j.procs.2018.05.192.

[30] D. P. Prakyath, S. A. Karthik, S. Prashanth, A. H. V. Krishna and V. Siddhartha, "Novel Approach for Gridding of Microarray Images". *In: Goyal, D., Bălaş, V.E., Mukherjee, A., Hugo C. de Albuquerque, V., Gupta, A.K. (eds) Information Management and Machine Intelligence. ICIMMI 2019. Algorithms for Intelligent Systems*. Springer, Singapore, doi: 10.1007/978-981-15-4936-6_41.

[31] M. A. Ali, G. C. Karmakar and L. S. Dooley, "Fuzzy Clustering for Image Segmentation Using Generic Shape Information", *Malaysian Journal of Computer Science*, Vol. 21, No. 2, 2008, 122–138. doi: 10.22452/mjcs.vol21no2.5.

[32] A. Dey, R. Pradhan, A. Pal, & T. Pal, "A genetic algorithm for solving fuzzy shortest path problems with interval type-2 fuzzy arc lengths", *Malaysian Journal of Computer Science*, vol. 31, no. 4, pp. 255-270, 2018, doi: 10.22452/mjcs.vol31no4.2.

[33] M. R. Zare., W. C. Seng and A. Mueen, "Automatic classification of medical x-ray images", *Malaysian Journal of Computer Science*, Vol. 26, No. 1, 2013, pp. 9-22, doi: 10.22452/mjcs.vol26no1.2.

[34] H. J. G., Opeña and J. P. T. Yusiong. "Automated Tomato Maturity Grading Using ABC-Trained Artificial Neural Networks", *Malaysian Journal of Computer Science*, Vol. 30, No. 1, 2017, pp. 12-26, doi: 10.22452/mjcs.vol30no1.2.