NEURO-FUZZY BASED MRESNET (NFMRESNET) CLASSIFICATION FOR BRAIN TUMOR IMAGE DATASET

R. Vinayaga Moorthy[1], R. Balasubramanian[2]

[1]Research scholar, Department of Computer Science & Engineering, Manonmaniam Sundaranar University, Tirunelveli, Tamil Nadu, India-627 012

[2]Professor, Department of Computer Science & Engineering, Manonmaniam Sundaranar University, Tirunelveli, Tamil Nadu, India-627 012

Email: vinayagamoorthy3@gmail.com[1],rbalus662002@yahoo.com[2]

Article History: **Received:** 16.04.2023 **Revised:** 03.05.2023 **Accepted:** 19.06.2023

Abstract: *Brains are enormous and complex organs that control our nervous systems and contain about 100 billion nerve cells. The brain is an essential organ. A brain abnormality could put human health at risk. Tumors in the brain are among the most serious of these abnormalities. An uncontrollable growth of brain cells inside the skull causes this serious form of cancer. Generally, tumor cells exhibit heterogeneity, making them difficult to classify. In order to decide on the correct medication, it is essential that tumors are detected early, and their location, size, and types must also be assessed. Developing systems that incorporate human expertise is becoming increasingly popular using Soft Computing. Image processing and cytology are used more often to diagnose disease. Correct diagnosis is essential in treating and curing diseases. This paper proposes a fuzzy logic based brain tumor classification method that can be used for proper treatment planning. This paper provides detailed analysis of the advantages of the hybrid method, demonstrating the fact that when Neuro-Fuzzy Neural is paired with MResNet (NFMResnet), there is a significant increase in classification accuracy. The NFMResnet contains convolutional layers, pooling layers, and fully-connected layers, as well as a Fuzzy Self-Organization Layer. Using MResNet and fuzzy logic, the model handles uncertain and imprecise input patterns. Three independent steps are involved in training the NFMResnet. Three independent steps are involved in training the NFMResnet.*

Keywords: *Fuzzy C-Means Clustering, MResnet, Genbourta, NFMResnet*

1. INTRODUCTION

Tumors are swellings that form lumps or masses in the body. A tumor is a lump or mass produced by a pathological process within the body. It can be referred to as a swelling. A neoplasm is characterized by tumors. Cancers are usually referred to as neoplasms. In some cases, doctors may confuse infections with tumors when performing image diagnosis. In some cases, body cells may lose their ability to respond to physiological signals. Such tissues are controlled by physiological mechanisms. This results in tumors getting into place. Tumors are formed from uncontrolled growth of body cells and are referred to as neoplastic tissue. Among the structures in the brain connected to tumors are neurons, blood vessels, skulls, lymphatic tissues, pituitaries, and pineal glands.

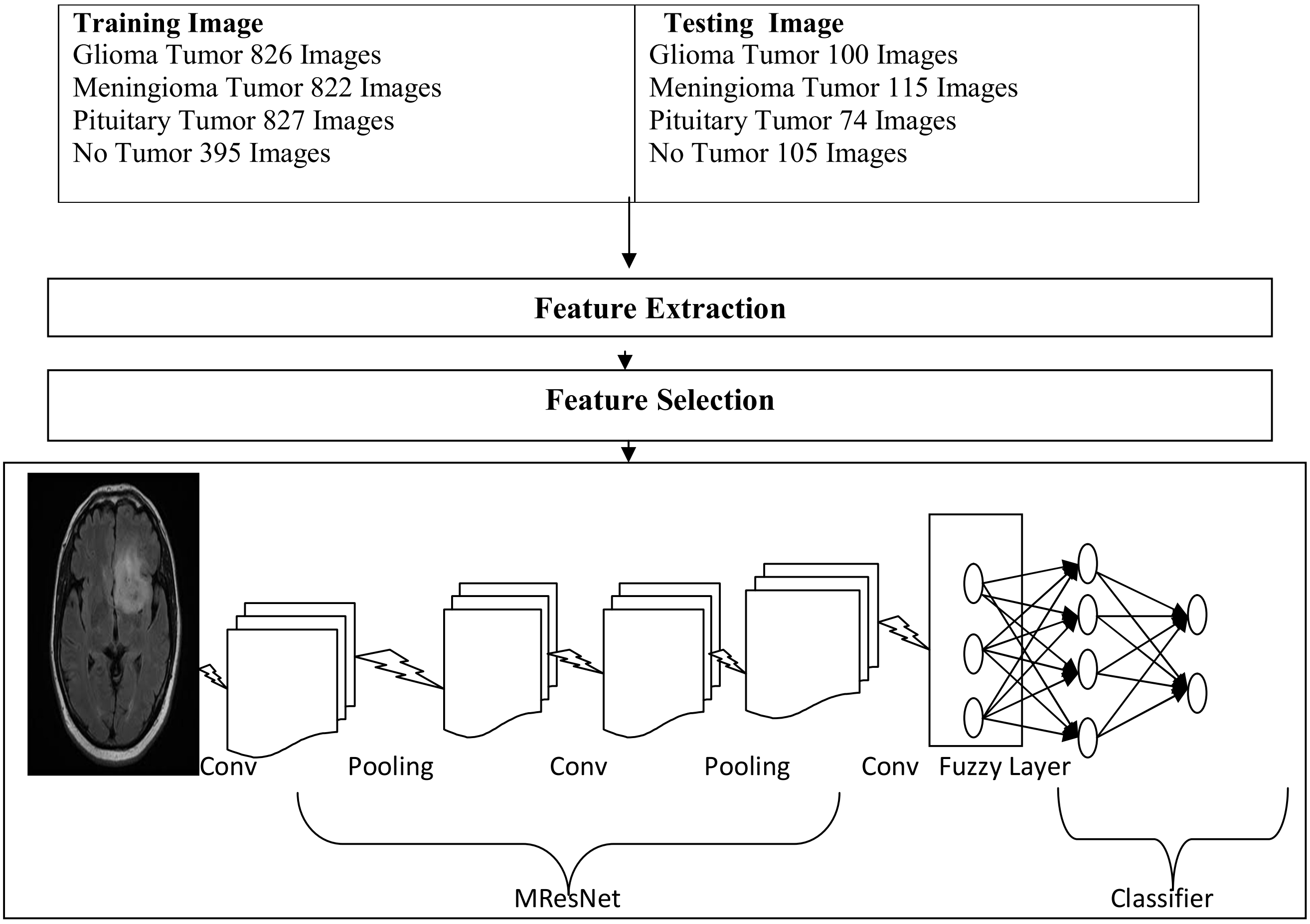

Fig 1: Classification Process

Although images of complex real-world scenes or complex objects are difficult to classify, it is still difficult to detect the boundaries between classes. There is often uncertainty in the representation of these classification objects, and they have complex structures with overlapping, non isolated classes.

The use of MResNet in image classification is one of the most powerful approaches today. In MResNet architectures, inputs are explicitly assumed to be images, allowing certain abstract properties to be encoded.

Fuzzy classification, unlike classical classification, has continuous boundaries with overlapping areas between neighboring classes. The degree to which an object belongs to different classes determines its classification. This is a useful approach for a wide variety of applications, as well as for representing complex feature spaces in a simple way.

1.1 Feature Extraction

It is easier to comprehend an image if we extract its most significant features. Feature extraction is the process of identifying features. An image texture feature is extracted using GLCMs (grey-level co-occurrence matrix). In addition to enhancing the details of the image, it gives interpretations to it. In computer vision and image processing, shape descriptors are a powerful tool used to match objects, classify them, recognize and identify them. Histogram-based detection is more specific when combined with other detection methods such as shape analysis and edge finder based on Fourier transforms.

1.2 Feature Selection
The Boruta Algorithm and the Genetic Algorithm are combined in a hybrid algorithm. In terms of selecting optimal feature subsets from a limited set of features, Genboruta uses the advantages of existing algorithms. In order to select the most appropriate features from the data extracted from feature extraction, the feature selection method is applied. The most significant features are selected using the Genboruta algorithm.

1.3 Fuzzy Based Classification
Researchers have been paying a lot of attention to Deep Learning, the newest and most popular trend in the machine learning field. Throughout various fields, deep learning has been used as a powerful machine learning tool to solve complex problems, particularly those requiring highly accurate and sensitive results. Comparatively to classical classifications, fuzzy classifications have overlapping areas between neighboring classes. The degree to which an object belongs to different classes determines its classification. A simple representation of a complex feature space is provided by this approach, which can be used for a wide variety of applications.
Fuzzy logic can be incorporated into neural networks to make them more adaptable to cognitive uncertainties. A fuzzy neural network is a hybrid network whose outputs are called neural fuzzy, neuro-fuzzy or fuzzy-neuro networks. Fuzzy computations and neural networks are combined in hybrid systems Practically, fuzzy neural networks are more effective than fuzzy neural networks or ordinary (classical) neural networks, because fuzzy neural networks allow indeterminate and inaccurate information processing. The transition from one cluster to another can be more gradual with fuzzy clustering as it is more robust to outliers and noise in the data.

1.4 Fuzzy C-Means Clustering
It is possible with fuzzy clustering to group data points into more than one cluster with varying degrees of membership. The fuzzy clustering algorithm assigns membership degrees between 0 and 1 to each data point rather than assigning them to a single cluster like k-means or hierarchical clustering. If the data has a complex structure or overlapping class boundaries, fuzzy clustering can be useful. In addition to providing a more accurate understanding of the data structure, fuzzy clustering also allows for more detailed representation of relationships between data points and clusters.

2 LITERATURE SURVEY
For many years, artificial intelligence has struggled to solve problems that were deemed insoluble by deep learning. In addition to speech recognition [17], natural language processing [11], information retrieval [6], computer vision [5], biomedicine [5], and social media analysis [1], it is exceptionally adept at discovering intricate structures in high dimensional data.
Natural data in their raw form cannot be processed by conventional machine-learning techniques. Machine learning or pattern recognition systems have been constructed for decades with careful engineering and domain expertise. In order for a learning system (often a classifier) to detect or classify patterns in input data, the data has to be transformed into a suitable internal representation or feature vector. Deep learning techniques, which differ from conventional neural networks, use multiple hidden layers to determine representations needed for classification or detection based on raw data [20]. The methods used in deep learning include feedforward deep neural networks (DNNs)[7], convolutional neural networks (CNNs) [12], recurrent neural networks (RNNs) [16], spiked neural networks (SNNs) [9], long short-term memory recurrent networks (LSTMRNs) [18], stacked auto-encoders (SAEs)[21], deep belief networks (DBNs)[23], and restricted Boltzmann machines (RBMs)[13].
An adaptable neuro-fuzzy inference system (ANFIS) was recently proposed as a model for addressing this issue, and several successful attempts have been reported in the literature [2–4]. To form deep neurofuzzy systems (DNFS), these studies combined deep neural networks with fuzzy logic (FL). Through the use of fuzzy IF–THEN rules, this hybridization of DNN and FL effectively reduced uncertainty. It has been

rapidly growing in popularity since DNFS was introduced to solve a variety of real-world problems, including Ramasamy and Hameed [3] proposed fuzzy convolutional neural network (FCNN) using both FL and DNN to classify healthcare data into categories. There are two main parts of FCNN training: parameter initialization and fine-tuning. A FCNN classifier was used in this study to classify ambiguous or noisy data. According to the results of the study, the proposed FCNN method can easily remove uncertainties and noise from original data.

As Price et al. reported [22], using best-in-class pre-prepared models, AlexNet, VGG16, GoogleLeNet, Inception-v3, and ResNet-18, the fuzzy layers can be used for deep learning, enabling a wide selection of combinations and yields.

Another classifier reliant upon fuzzy logic and wavelet change in a brain network was depicted in this review. A layer in this classifier predicts the mathematical trademark related with marks or characterizations. The proposed classifier is utilized to analyze cerebrum growths [10].

Among the most exploited techniques in image processing is CNN. Clinical diagnosis has assumed an increasing significance in contemporary healthcare systems because it is capable of recognizing patterns in images.U-NET Convolutional Neural Network (CNN) classification methodology and edge detection fuzzy logic are used in this article in order to develop a method for the detection of brain tumors using edge detection and fuzzy logic [19].

3 METHODOLOGY

Anatomical and functional information about brain tumors contributes greatly to enhancing diagnoses and simplifying disease treatment planning in medical imaging applications. A brain tumor analysis can, however, be impacted by the presence of image artifacts such as noise, intensity in homogeneity, and partial volume effects. It is also necessary to consider the complex anatomy of the brain. Visual content is extracted from images for indexing and retrieval through feature extraction. Basic features of an image may be general in nature, such as color, texture, and shape, or they may be domain-specific. Features are extracted by reducing the number and creating a new set of them that have the same information as the originals, but that are completely different. These methods improve the accuracy of the classifier, minimize overfitting, allow visualization of data, and increase training speed.

Machine learning algorithms are applied to a subset of features in the data by feature selection (also known as subset selection). The best subset has the fewest dimensions that contribute to high accuracy; the rest are discarded.

Recent years have seen DL's performance improve in several domains. In DL models, multiple levels of information can be learned automatically from a large set of data. Their advantage is that they do not require a lot of effort for tuning the features and expert knowledge like traditional machine learning. DL has several architecture. Image processing uses CNN as a technique for recognizing patterns in images.

Fig 2: Proposed Fuzzy Based MResnet Classification

3.1 Feature Extraction

By analyzing images and objects, feature extraction methodologies extract features that represent various classes of objects. A classifier assigns features to their respective classes based on their features. A feature extraction algorithm reduces original data by identifying certain properties that separate one input pattern from another. In the extracted feature vector, the relevant properties of the image should be described in order to provide the classifier with the characteristics of the input type.

3.2 Features Optimization Using GenBoruta

This research relies on using a hybrid model that combines both a Genetic Algorithm and a Boruta Algorithm, with an original aim of grouping tests before selecting the small number of important variables.The use of a hybrid technique overcomes the disadvantages of each individual one [14].

Table 1: Selected Features

S.No	Genboruta (Features)		
1.	Surface Area	2.	Range
3.	Flatness	4.	Cluster shade
5.	Skewness	6.	Dissimilarity
7.	Uniformity	8.	Maximum Probability
9.	Contrast	10.	Variance
11.	Correlation	12.	Max Intensity

3.3 Modified Resnet (MResnet)

RESNET18 architecture consists of 18 layers. There are three layers of convolution, each using three kernels. Stack layers are added to the output; therefore, complex computations are not required with the MResNet algorithm because one or more layers are skipped. A shortcut connection for ResNet18 omits two layers. The design was based on Swish activation functions [15].

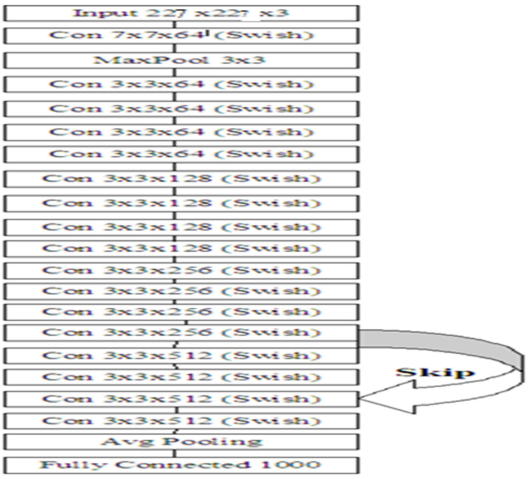

Fig 3: MResNet Classification Techniques

3.4. The Structure of an NFMResnet

The proposed MRNN's architecture features four types of layers: convolutional layer, pooling layer, self-organization (or fuzzy) layer, and fully connected layer. MResnet Fuzzy Neural Networks are built by stacking three parts:

- A MResnet network (convolutional and pooling Layers);
- The Self-Organization Layer (The Fuzzy Layer);
- A classifier (some fully-connected layers).

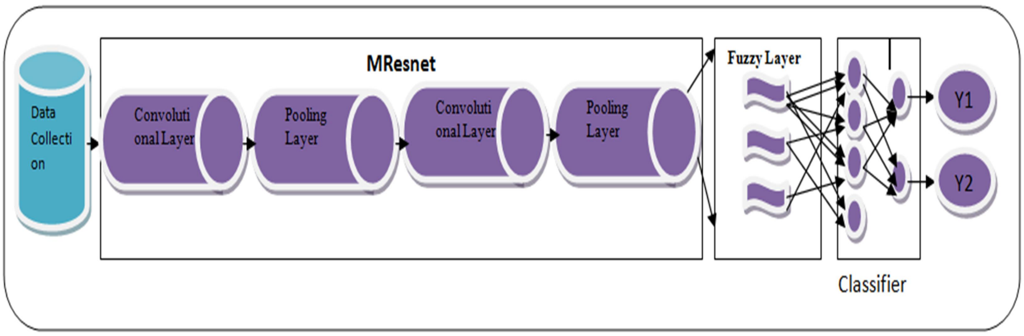

Fig 4: Struture of NFMResnet

To classify real-world objects and scene images, we propose an MResnet fuzzy neural network (NFMResnet). A self-organization layer is utilized to provide preprocessing in the proposed NFMResnet model; unlike a regular MResnet. To cope with uncertainties and ambiguities in input data, the proposed network incorporates the advantages of MResnet and FL Three layers of the NFMResnet are shown in Figure 4: the convolutional network, the self-organization layer, and the classifier layer. Below is a description of each part's functionality:

1 The first layer of the network is the convolutional network, which substitutes the pooling layer with the convolutional layer for abstraction at the high level.
2 Secondly, the fuzzy layer divides the input data into predetermined clusters before making a final clustering decision. Fuzzy layer output neurons are a representation of the fuzzy input cluster membership functions, with membership grades reflecting the degree to which data points are related to each cluster.
3 A classifier is used to calculate the class score as an output of the NFMResnet network, the third part of the network.

Fuzzy C-Means Clustering

Data clusters are detectable with the FCM algorithm, but these clusters do not have any order, making interpretation challenging. In this paper, the cluster prototypes are ordered on an easily visualizable small dimension space to increase the transparency of the clustering result. A regularization of the clusters can achieve this ordering. The original objective function of FCM is penalized in order to achieve such regularization. On a small dimensional space, cluster centers are laid out on a grid for easy visualization. Regularizing the fuzzy c-means function (FCM) results in the smoothness of this mapping.
NFMResnet uses a radial basis function to model the membership of an input vector x to each of the L clusters, whereas the number of neurons in the fuzzy layer is L.

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-2\frac{(x-m)^2}{2\sigma^2}} \qquad 1 \longrightarrow$$

In the above condition, m and σ - are two genuine qualities, where the focal point of a bunch is addressed as m, and σ - is utilized to obscure the limit level of a group. A compound interest expression arising in the study of compound interest is the Euler's number 'e'. The sum of infinite numbers can also be expressed in this way.

$$e = \sum_{n=0}^{\infty} n!$$

$$\mu l\big(\mathrm{x})^{(k)}\big) = f(s) = f(f\left(\sum\nolimits_{j=0}^{n} x_j^{(k)}\right)^2 \longrightarrow$$

$$\sum\nolimits_{l=0}^{l} \mu l\big(\mathrm{x})^{(k)}\big) = 1 \qquad 3 \longrightarrow$$

The hybrid network formed a vector consisting of degrees of belonging to the specific cluster centers based on the vector x = [x1, x2, ..., xn] fed to its input: [μ1(x),μ2(x), ..., μL(x)]. In the "fuzzy layer", the outputs of neurons are used as inputs to the classifier, which has been conditioned to satisfy the normalization condition (3) for each training sample vector x(k). An input to the classifier is the output of neurons in the "fuzzy layer".
NFMResnet works in three stages: first, it transforms an image into a vector of high-level characteristics, second, the fuzzy layer distributes the input data into fuzzy clusters; thirdly, the final fully connected layer performs the classification by assigning a label to each group of clusters based on the result class.

3.5 The Training of the NFMResnet

MResnet's training process involves three independent steps for each component of the neural network.
The MResnet network is first trained by backpropagation to form some abstract properties of the input image .In today's world, most "pre-trained" models have already been trained on a large amount of data from a related domain.
It is the process of tuning the fuzzy layer parameters, called self-organization,that is the second part of the process. Fuzzy Layers have a self-organizing nature. An unsupervised competitive learning scheme is used to train it. In "fuzzy layers", centers of clusters are self-organized.

Training the classifier is the third part. The MResnet and fuzzy layers have stable parameters. Tuning is only done on the weights of fully connected layers. A standard backpropagation algorithm is used to train the classifier.
A pixel array of an image is fed into the NFMResnet input after NFMResnet has completed all three parts of training. y = [y1, y2, ..., yp] represents a vector that represents whether a given image belongs to each class (class scores) in the input image. Images are assigned to classes based on their maximum score.

Conv Layer 1	227x277x3	64	7x7	112x112x64	Swish
Max-pool	112x112x64	64	3x3	56x56x64	Swish
Conv Layer 2	56x56x64	64	3x3	56x56x64	Swish
Conv Layer 3	56x56x64	64	3x3	56x56x64	Swish
Conv Layer 4	56x56x64	64	3x3	56x56x64	Swish
Conv Layer 5	56x56x64	64	3x3	56x56x64	Swish
Conv Layer 6	56x56x64	128	3x3	28x28x128	Swish
Conv Layer 7	28x28x128	128	3x3	28x28x128	Swish
Conv Layer 8	28x28x128	128	3x3	28x28x128	Swish
Conv Layer 9	28x28x128	128	3x3	28x28x128	Swish
Conv Layer 10	28x28x128	256	3x3	14x14x256	Swish
Conv Layer 11	14x14x128	256	3x3	14x14x256	Swish
Conv Layer 12	14x14x128	256	3x3	14x14x256	Swish
Conv Layer 13	14x14x128	256	3x3	14x14x256	Swish
Conv Layer 14	14x14x128	512	3x3	7x7x512	Swish
Conv Layer 15	7x7x512	512	3x3	7x7x512	Swish
Conv Layer 16	7x7x512	512	3x3	7x7x512	Swish
Fuzzy Layer	7x7x152	512	3x3	7x7x512	Swish
Average pool	7x7x152	512	7x7	1x1x512	Swish
Layer 18	1x1x152	-	-	1000	Softmax

Skip

Fig 5: Architecture of Proposed NFMResnet Classification Technique

NFMResnet **Algorithm**

NFMResnet Algorithm

Step 1: Insert the image (277x277x3).
Step 2: Convolutional layer 1(7x7size 64 filters are used). It generates a 112x112x64 pixel feature map.
Step 3: The Max pooling (3x3 size 64filters are used). The output is a 56x5x64 pixel feature map.
Step 4: Convolutional layer 2(3x3size 64 filters are used).). It generates a 56x56x64 pixel feature map.
Step 5: Convolutional layer 3(3x3size 64 filters are used). It generates a 56x56x64 pixel feature map.
Step 6: Convolutional layer 4(3x3size 64 filters are used). It generates a 56x56x64 pixel feature map.
Step 7: Convolutional layer 5(3x3size 64 filters are used). It generates a 56x56x64 pixel feature map.
Step 8: Convolutional layer 6(3x3size 128 filters are used). It generates a 28x28x128 pixel feature map.
Step 9: Convolutional layer 7(3x3size 128 filters are used). It generates a 28x28x128 pixel feature map.
Step 10: Convolutional layer 8(3x3size 128 filters are used). It generates a 28x28x128 pixel feature map.
Step 11: Convolutional layer 9(3x3size 128 filters are used).It generates a 28x28x128 pixel feature map.
Step 12: Convolutional layer 10(3x3size 256 filters are used). It generates a 14x14x256pixel feature map.
Step 13: Convolutional layer 11(3x3size 256 filters are used). It generates a 14x14x256 pixel feature map.
Step 14: Convolutional layer 12(3x3size 256 filters are used). It generates a 14x14x256 pixel feature map.
Step 15:.Convolutional layer 13(3x3size 256 filters are used). It generates a 14x14x256 pixel feature map.
Step 16: Convolutional layer 14(3x3size 512 filters are used). It generates a 7x7x512 pixel feature map.
Step 17: This layeris omitted from the Skip connections of MResNet.
Step 18: This layeris omitted from the Skip connections of MResNet.
Step 19:.**Fuzzy Layer** 17(3x3size 512 filters are used). It generates a 7x7x512 pixel feature map.
Step 20: The average pooling (7x7 size 512 filters are used). The output is a 1x1x512 pixel feature map.
Step 21: This layer is the output layer.It uses a Softmax activation function.

4. RESULTS

CFNN is used in some experiments. An image is classified as either having a tumor or not using the model. The dataset used here is Kaggle's ' Brain tumor '. The training set contains 2,870 MRI brain tumor images, while the test set contains 394.

In Figure 6, we show some samples of images from the 'Brain Tumor' dataset.

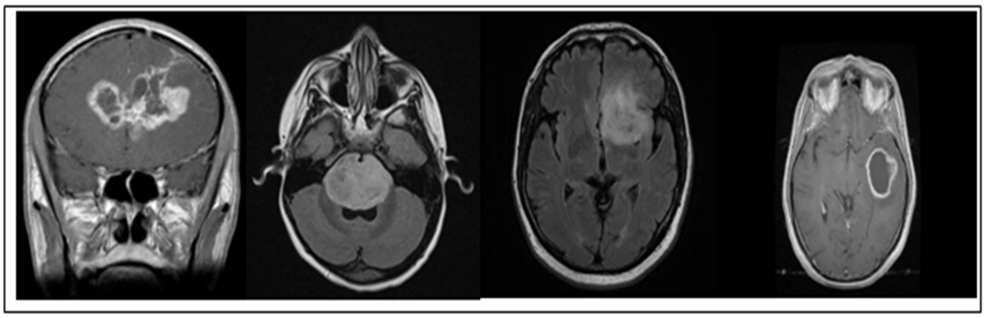

Fig 6: Sample MRI Brain Tumor Image

The first step is to use a pretrained model that recognizes a wide range of images and then fine-tune it for binary classification. In order to achieve a simple yet powerful neural network architecture, we chose Lenet, AlexNet, VGG Net, and Resnet models pretrained on the Kaggle dataset. To train the NFMResnet model, we took three independent steps:

1. Analyzing brain tumor images to classify them using Lenet, AlexNet, VGG Net, and Resnet models (stochastic optimization algorithm: Adam). Resources are required for the MResnet training.
2. Clustering based on fuzzy c-means (self-organizing fuzzy layer). Multiple clusters have been created with the data set, each with a different number of clusters. Using the Fuzzy Partition Coefficient, we choose the number of clusters when it is maximized (FPC varies from 0 to 1, with 1 being the best. It is a metric that measures how well the clustering model describes the data).
3. A stochastic optimization method called Adam is used for classifier training. The parameters of the MResnet and fuzzy layers were stable while only the weights of the fully-connected layers were being tuned.

The results of experiments show that incorporating the fuzzy layer into MResnet improve classification problem quality (accuracy) despite the regular CNN not showing exceptional accuracy.

4.1 Evaluation Metrics

$$\text{Accuracy} = \frac{\text{True}_{\text{positive}} + \text{True}_{\text{negative}}}{\text{True}_{\text{positive}} + \text{True}_{\text{negative}} + \text{False}_{\text{positive}} + \text{False}_{\text{negative}}} \longrightarrow (4)$$

$$\text{Precision} = \frac{\text{True}_{\text{positive}}}{\text{True}_{\text{positive}} + \text{False}_{\text{positive}}} \longrightarrow (5)$$

$$\text{Recall} = \frac{\text{True}_{\text{positive}}}{\text{True}_{\text{positive}} + \text{False}_{\text{negative}}} \longrightarrow (6)$$

$$\text{Specificity} = \frac{\text{True}_{\text{negative}}}{\text{True}_{\text{negative}} + \text{False}_{\text{positive}}} \longrightarrow (7)$$

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \longrightarrow (8)$$

Table 6: Classification Performance Analysis

Algorithm	Accuracy	Precision	Recall	Specificity	F1-Score
Lenet	84.48	89.66	81.25	88.48	85.25
Alexnet	87.66	93.1	84.38	92.31	88.52
VGG 16	89.66	96.55	84.85	96	90.32
ResNet 16	96.4	95.7	95	93	94.2
MResnet	96.5	92.3	95	93	94.12
NFMResnet	**98.8**	**93.3**	**95.9**	**94.6**	**95.9**

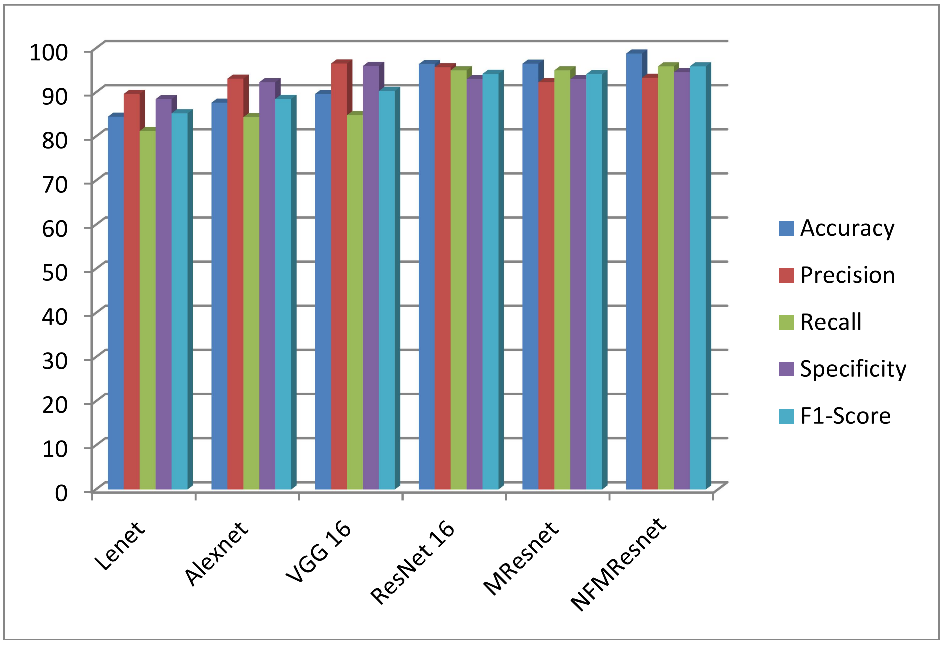

Fig 3: Classification Graphical Representation

5. CONCLUSION

A brief discussion of all relevant data must precede the conclusion of this extensive research. We compared its performance against pretrained LeNet, AlexNet, VGGNet, and ResNet, MResnet for the brain tumor analysis. Three thousand two hundred sixty-four records make up the Kaggle brain tumor data set. A stratified sampling method was used to divide the data set into 10 mutually exclusive partitions for model building and evaluation. The training partitions were used for seven, while the testing partitions were used for four. For each of the four models, accuracy, precision, recall, and F1Score are calculated.

Therefore, this paper presents an image classification model based on Neuro fuzzy MResnet (NFMResnet). In terms of fuzzy C- Maens Cluster, fuzzyness is incorporated into the structure of the network. MResnet is combined with fuzzy logic in the proposed model for handling uncertainty and imprecision. Experiments measuring the effectiveness of NFMResnet have been conducted and indicate that the NFMResnet could provide better accuracy.

REFERENCES

1. Andrei Romascanu, Hannah Ker, Renee SieberSarah Greenidge, Sam Lumley, Drew Bush, Stefan Morgan, Rosie Zhao and Mikael Brunila, "Using deep learning and social network analysis to understand and manage extreme flooding" , John Wiley & Sons, pp.251-261,2020.
2. Angelica I. Aviles, Samar M. Alsaleh, Eduard Montseny, Pilar Sobrevilla & and Alicia Casals, "A Deep-Neuro-Fuzzy Approach for Estimating theInteraction Forces in Robotic Surgery", IEEE, pp.1113-1119,2016.
3. Balamurugan Ramasamy, Abdul Zubar Hameed, "Classification of healthcare data using hybridised fuzzy and convolutional neural network", Healthcare Technology Letters, Volume 6, Issue No. 3, pp. 59–63, 2019.
4. Chaimae El Hatri, Jaouad Boumhidi, "Fuzzy deep learning based urban traffic incident detection", ScienceDirect, Elsevier, pp.1-8,2017.
5. Eralda Nishani, Betim Cico, "Computer Vision Approaches based on Deep Learning and Neural Networks: Deep Neural Networks for Video Analysis of Human Pose Estimation", IEEE, PP. 11-15, 2017.
6. Jiafeng Guo, Yixing Fan, Liang Pang, Liu Yang, Qingyao Ai, Hamed Zamani, Chen Wu, W. Bruce Croft, Xueqi Cheng, "A Deep Look into neural ranking models for information retrieval' , Information Processing and Management, Elsevier Ltd, pp.1-20,2019.
7. Maximilian Schaedler, Christian Bluemm, Maxim Kuschnerov, Fabio Pittala, Stefano Calabro and Stephan Pachnicke, "Deep Neural Network Equalization for Optical Short Reach Communication" , Applied Science, MDPI, Volume 9, pp.1-14,2019.
8. Michael Wainberg, Daniele Merico, Andrew Delong & Brendan J Frey, "Deep learning in biomedicine", nature biotechnology, Volume 36 ISSUE Number 9,PP.829-838,2018.
9. Mohd Hafizul Afifi Abdullah, Muhaini Othman, Shahreen Kasim, Siti Aisyah Mohamed, "Evolving spiking neural networks methods for classification problem: a case study in flood events risk assessment", Indonesian Journal of Electrical Engineering and Computer Science, Vol. 16, Issue No. 1, pp. 222-229, 2019.
10. Mohsen Ahmadi ,Fatemeh Dashti Ahangar,Nikoo Astaraki,Mohammad Abbasi ,and Behzad Babaei, "FWNNet: Presentation of a New Classifier of Brain Tumor Diagnosis Based on Fuzzy Logic and the Wavelet-Based Neural Network Using Machine-Learning Methods", Computational Intelligence and Neuroscience, Hindawi, pp1-13,2021.
11. N I Widiastuti, "Convolution Neural Network for Text Mining and Natural Language Processing" ,Materials Science and Engineering, IOP Publishing, pp.1-6,2019.
12. Najwa Altwaijry and Isra Al-Turaiki, "Arabic handwriting recognition system using convolutional neural network", Neural Computing and Applications, Springer, pp.1-13, 2020.
13. Nan Zhang , Shifei Ding , Jian Zhang , Yu Xue, "An overview on restricted boltzmann machines", Neurocomputing, pp.1-30, 2017.
14. R.Vinayaga Moorthy, Dr.R.Balasubramanian, "An Efficient Genetic Boruta(GenBoruta) Algorithm Based Feature Selection on Brain Tumor Dataset" , International Journal of Mechanical Engineering, Vol. 7,Issue No. 6,pp.694-712, 2022.
15. R.Vinayagamoorthy, Dr.R.Balasubramanian, "A Modified Resnet (MRestNet) based Classification for Brain Tumor Dataset", NeuroQuantology, Volume 20, Issue 15,Page 7750-7767, 2022.
16. Robin M. Schmidt, "Recurrent Neural Networks (RNNs):A gentle Introduction and Overview" , arXiv, pp. 1-16, 2019.
17. S. Sharmadha, K. Shivani, K. Shruthi, B. Bharathi and S. Kavitha, "Automatic Speech Recognition Using Deep Neural Network" , Advances in Intelligent Systems and Computing, Springer, Volume 1118, pp. 353-361,2019.
18. Said Jadid Abdulkadir, Hitham Alhussian, Muhammad Nazmi, Asim A Elsheikh, "Long Short Term Memory Recurrent Network for Standard and Poor's 500 Index Modeling" , International Journal of Engineering & Technology, Volume 7,Issue No 4.15,pp. 25-29, 2018.

19. Sarmad Maqsood, Robertas Damasevicius, Faisal Mehmood Shah, "An Efficient Approach for the Detection of Brain Tumor Using Fuzzy Logic and U-NET CNN Classification" , Computational Science and Its Applications, Page.105–118, 2021.
20. Yann LeCun, Yoshua Bengio & Geoffrey Hinton, "Deep learning", Nature, Volume 521, pp.436-444, 2015.
21. Yi Qiu, Yiyang Dai, "A Stacked Auto-Encoder Based Fault Diagnosis Model for Chemical Process", Eindhoven, Elsevier, pp.1303-1308, 2019.
22. Yu-Jun Zheng, Member, Wei-Guo Sheng, Xing-Ming Sun, and Sheng-Yong Chen, "Airline Passenger Profiling Based on Fuzzy Deep Machine Learning" , IEEE transactions on neural networks and learning systems,pp.1-13,2016.
23. Yuming Hua, Junhai Guo, Hua Zhao, "Deep Belief Networks and Deep Learning" , IEEE,pp.1-4 ,2015.