JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 2, 2022, p. 2569 - 2576
https://publishoa.com
ISSN: 1309-3452

CNN-Fuzzy Rule Based System for Classifying Medical Imaging Process

M. Vijaya*, A. Aruna**
*Head and Prof., PG and Research Dept of Mathematics, Marudupandiyar college, Thanjavur
**Ph.D. Scholar, Dept of Mathematics, Marudupandiyar college, Thanjavur
(Affiliated to Bharathidasan University, Trichy)

ABSTRACT
Diagnosing medical data could be done through an expert physician or by radiologists, Evolving artificial intelligence support in decision systems in order to diagnose medical data including textual and images. In this paper, the convolutional neural network and fuzzy rule based system has been proposed. Detection and classification risk of brain tumor is considered for the diagnosis. Finding tumor and tumor risk is essential and crucial with a computer-aided system.Magnetic resonance imaging (MRI) is a technique in the medical field to get a detailed image of internal organs of the human body using the magnetic field. Brain tumor imaging could be done using the techniques Computed tomography and MRI and Convolution Neural Network, a popular deep learning technique that performs an excellent result recently in image classification and fuzzy rule-based method is used to analyze the risk of tumor.

Keywords:- Artificial Intelligence, Neural Network, Convolutional Neural Network, Fuzzy rule-based system

1. Introduction
According to “Brain and other central nervous system tumor statistics”, 2021,[1] Brain and central nervous system (CNS) tumors are the most fatal cancers among other cancers and it causes substantial morbidity and mortality in the United States[1] and other parts of the world. Medical image processing [2] is broadly used for detection of brain tumors and brain tumors have variants such as Meningioma, Glioma, Pituitary [3]. There are computer aided systems that help consultants in analyzing and finding the brain tumor , Convolutional Neural Network is the most accurate classification technique [4] in medical image processing recently. Evolution of Artificial Intelligence and Deep learning progress to significant results in convolutional networks.

Convolutional Neural Network (CNN) is a deep learning method that is mainly used as image processing[5] technique, convolution method is used to find a pattern in the given image input followed by a set of processes. CNN is the mathematical approach that combined with the convolution, pooling, and fully connected layers[6]. Each layer has its own derivations and methods. CNN performs excellent results when compared to traditional machine learning techniques and other image processing techniques. Deep CNN has achieved significant results in recent years on image processing or computer vision problems.Thus, emergence to large image datasets such as ImageNet with 10+ million images and 20,000+ classes [7].

Fuzzy logic theory was introduced by L.A. Zadeh in 1965. Fuzzy logic comes in when conventional logic fails. It is a computational paradigm which is based on human thinking. An important concept in fuzzy logic is the application of linguistic variables i.e. variables whose values are words or sentences in natural language (Zadeh, 1975). The fuzzy reasoning approach has found a wide application in designing of certain complex industrial and management systems which cannot be modeled precisely under various assumptions and approximations. One of the famous applications of fuzzy logic and fuzzy set theory is the Fuzzy inference system (FIS) (Guillaume, 2001). FIS are knowledge-based or rule-based systems that contain descriptive if-then rules created from human knowledge and experience (Kharola and Gupta, 2014). A basic fuzzy architecture consists of three components: fuzzifier, FIS and defuzzifier. Fuzzifier maps crisp numbers into fuzzy sets whereas the defuzzifier maps output sets into crisp numbers[8]. The FIS represents the core of fuzzy logic controllers (FLC's). It is built of rule-base and data-base, which constitute the knowledge base and inference engine. Fuzzy logic controller proceeds in three steps. First step is fuzzification. This crisp variable is converted to a fuzzy variable. In the second

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 2, 2022, p. 2569 - 2576
https://publishoa.com
ISSN: 1309-3452

step some rules are set up in the form of If Then an inference system works. The third step is defuzzification. In this resulting fuzzy output is converted back into a crisp variable[9]. Fig. 3.1. describes the fuzzy system.

2. Literature Review

There are plenty of real time systems proposed independently with fuzzy rule based systems and Convolutional Neural Network models. There is only a little literature that proposes a hybrid model which proposes a combination of convolutional neural network and fuzzy and it turns to remarkable results as well, let's come across a few of them in this section.

Hind R. Mohammed et al. [10] proposes *Hybrid Mamdani Fuzzy Rules and Convolutional Neural Networks for Analysis and Identification of Animal Images*, The built system applies fuzzy rules to detect the image and applies the CNN also the proposed fuzzy method has achieved an accuracy rate for identifying and recognizing of a moving objects with 98%. Several papers also proposes mixed implementation of fuzzy and neural network which is become a tightly coupled system, however it yields good results in many intelligent systems as combined solution, Tuan-Linh Nguyen et al.[11] proposed a multimodal framework for emotion understanding with the adaptive neural and fuzzy inference system that generates rules to classify emotions. For the understanding emotion concatenated audio, visual and text features extracted with the help of proposed convolutional neuro-fuzzy network system. There are other fuzzy and neural fusion systems proposed in real-time implementations to predict the traffic flow with uncertain Accident information[12] and in predicting electric load systems [13].

3. Methodology

The proposed system is a combined model of decision support system for detecting tumors using convolutional neural networks followed by classifying the risk using a fuzzy inference system, if detected as ‘yes’. The proposed system (Fig. 3.1.) has two major blocks, convolutional neural network (CNN) and Fuzzy inference system.

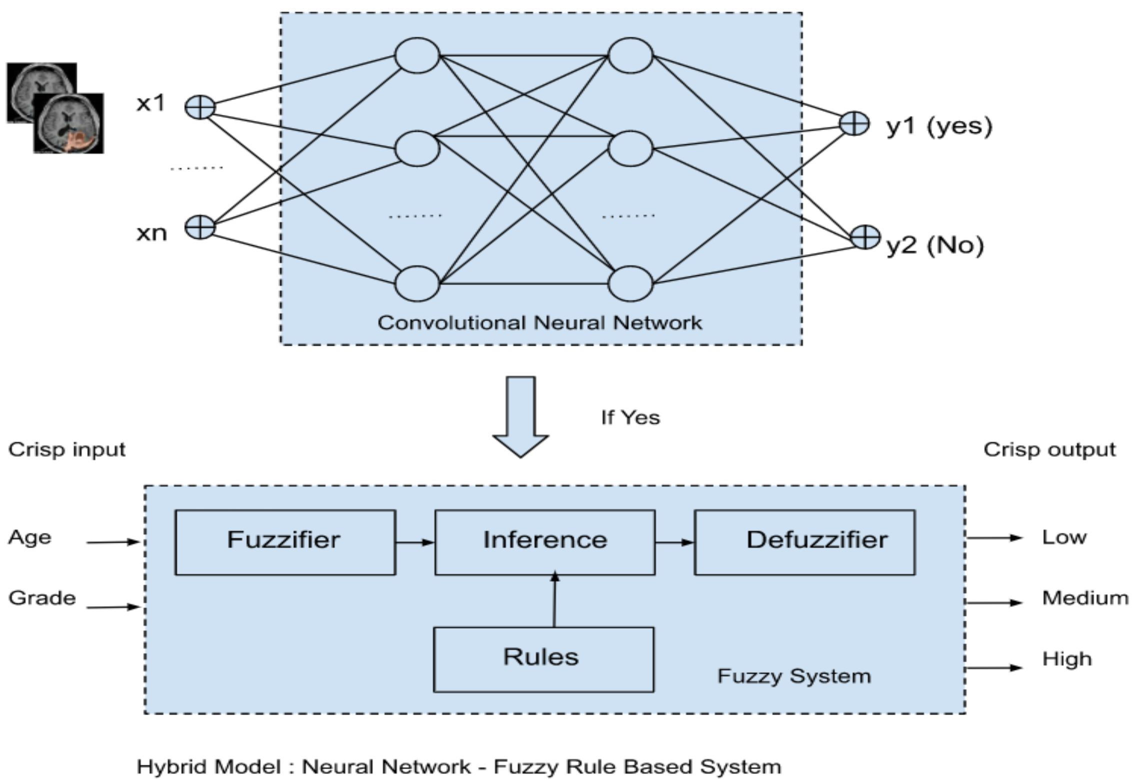

Fig. 3.1. Proposed system

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 2, 2022, p. 2569 - 2576
https://publishoa.com
ISSN: 1309-3452

3.1. Convolutional Neural Network (CNN)

Convolutional neural network(CNN) is inspired by the biological thought process i.e. multilayer perceptron in neural network and CNN is the feed forward neural network that performs with excellent results in pattern recognition applications in recent years, the representation of CNN is described in fig. 3.2.CNN has major operations such as convolution, activation, pooling and classification. convolution is a mathematical linear operation which multiplies weights with the input images represented in metrics, activation helps to make an attention in nodes to support decision at the end of every layer, sigmoid, tanh, ReLu are some of the mostly repeatedly used activation methods. Pooling is downsizing techniques using min or max methods, lastly classification layer where decision is made. During the training, backpropagation is applied and weights are adjusted to correct the results as given input.

We have a total of 2430 sample images, the images were distributed for training, validation and testing in the ratio of 60%, 20% and 20% respectively, thus the total sample was divided into 1518, 506 and 506 nos. Performance of convolutional neural network is measured by Precision, Recall, F1-score and Confusion matrix as given below,

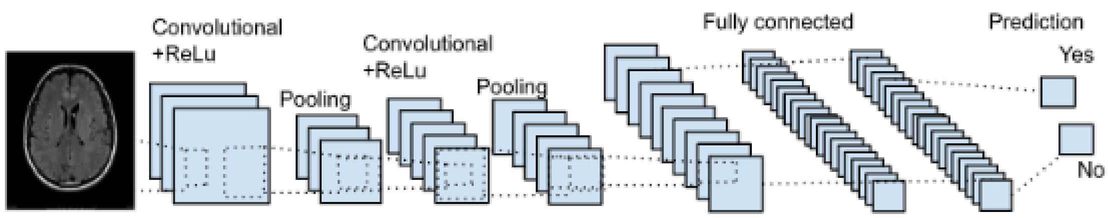

Fig. 3.2. Convolutional Neural Network

Precision = TP / (TP+FP)
Recall = TP / (TP+FN)
Accuracy = (TP + TN) / (TP+TN+FP+FN)
F1-Score = 2TP / (2TP + FP + FN)
Where TP = True positive, FP = False Positive, TN = True Negative and FN = False Negative

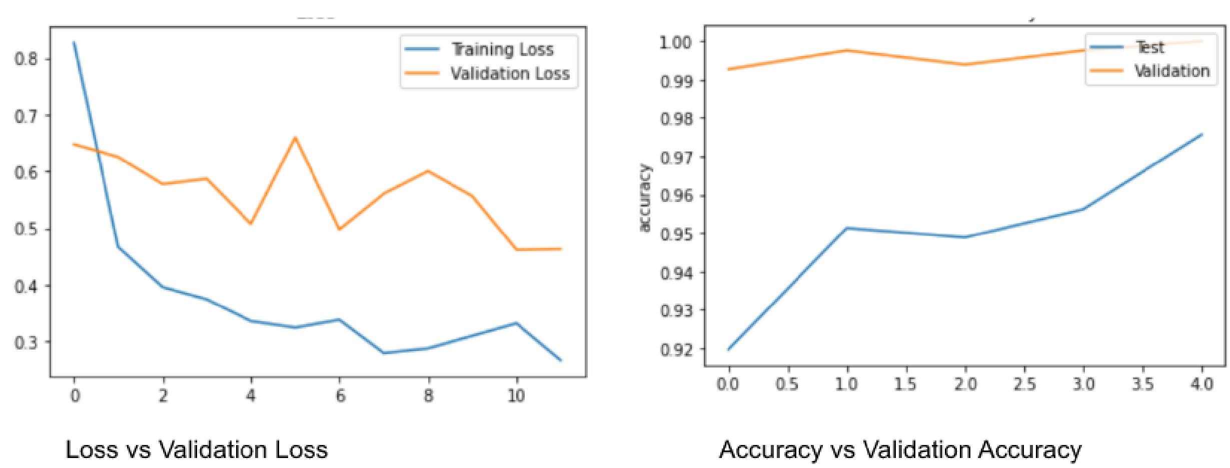

Fig. 3.3. Accuracy and loss

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 2, 2022, p. 2569 - 2576
https://publishoa.com
ISSN: 1309-3452

		Actual Values	
		Yes	**No**
Predicted Values	**Yes**	**1490**	**60**
	No	**106**	**874**

Table 3.1. Confusion Matrix

3.2. Fuzzy rule-based system

Fuzzy rule based systems are one of the most important areas of application of fuzzy sets and fuzzy logic. Extension of classical rule-based systems, these have been successfully applied to a wide range of problems in different domains for which uncertainty exists in multiple ways. Fuzzy rule based systems are rule based systems, where fuzzy sets and fuzzy logic are used as tools for representing different forms of knowledge about the problem for modeling the interactions and relationships existing between its variables. Fuzzy linguistic descriptions are formal representations of systems made through fuzzy IF-THEN rules. They encode knowledge about a system in statements of the form IF(a set of conditions) are satisfied THEN(a set of consequences) can be inferred. Fuzzy IF-THEN rules are coded in the form,

IF (x_1 is A1, x_2 is A2 ,....,x_n is An) THEN (y_1 is B1, y_2 is B2 ,..., y_n is Bn).

Where linguistic variables □□ , □□ take the values of fuzzy sets A□ and B□ respectively.

A collection of rules referring to a particular system is known as a fuzzy rule base. If the conclusion C to be drawn from a rule base R is the conjunction of all the individual consequents C□ of each rule, then

$$C = C1 \cap C2 \cap \ldots \cap Cn$$

where

$$\mu_c(y) = \min(\mu_{c1}(y), \mu_{c2}(y), \ldots, \mu_{cn}(y)), \qquad \forall\, y \in Y$$

Where Y is the universe of discourse.

On the other hand, if the conclusion C to be drawn from a rule base R is the disjunction of the individual consequences of each rule , then

$$C = C1 \cup C2 \cup \ldots \cup Cn$$

Where

$$\mu_c(y) = \max(\mu_{c1}(y), \mu_{c2}(y), \ldots, \mu_{cn}(y)), \qquad \forall\, y \in Y$$

Where Y is the universe of discourse.

3.1 Application:

Deciding the Risk of the patient using a Fuzzy rule based system.

The rules are framed under the Age and the Grade :

Rule 1: If (Grade is L) and (Age is L) then R is L:
Rule 2: If (Grade is L) and (Age is M) then R is L
Rule 3: If (Grade is L) and (Age is H) then R is L
Rule 4: If (Grade is M) and (Age is L) then R is L
Rule 5: If (Grade is M) and (Age is M) then R is M

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 2, 2022, p. 2569 - 2576
https://publishoa.com
ISSN: 1309-3452

Rule 6: If (Grade is M) and (Age is H) then R is H
Rule 7: If (Grade is H) and (Age is L) then R is H
Rule 8: If (Grade is H) and (Age is M) then R is H
Rule 9: If (Grade is H) and (Age is H) then R is H

Key:
R - Risk
L - Low
M - Medium
H - High

Computation of fuzzy membership value

For the fuzzification of inputs, that is, to compute the membership for the antecedents, the formula is illustrated in figure 3.4.

Delta 1 = x-point 1
Delta 2 = point 2-x
If (Delta 1 ≤ 0) or (Delta 2 ≤ 0) then degree of membership = 0
Else degree of membership = min{Delta 1 * slope 1, Delta 2 * slope 2, max }

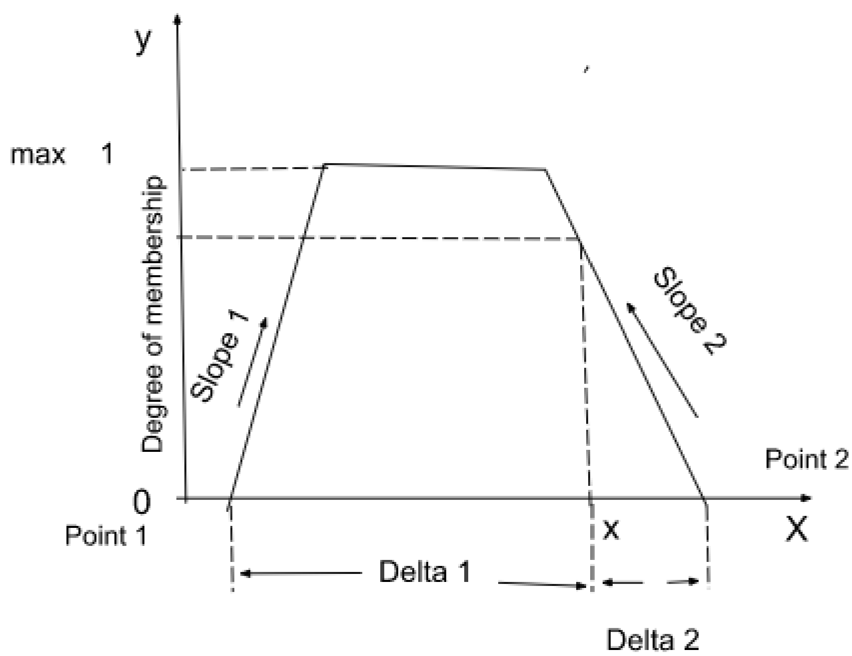

Fig. 3.4. Representation of degree of membership

Here, x which is the system input has its membership function values computed for all fuzzy sets. For example, the system input Age of the patients deals with three fuzzy sets, namely H - High, M - Medium, L - Low. The other input Grade size deals with three fuzzy sets, namely H - High, M - Medium, L - Low. The computation of the fuzzy membership values for the Age of the patients (x = 75), the qualifying fuzzy sets are shown in the figure 3.5.

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 2, 2022, p. 2569 - 2576
https://publishoa.com
ISSN: 1309-3452

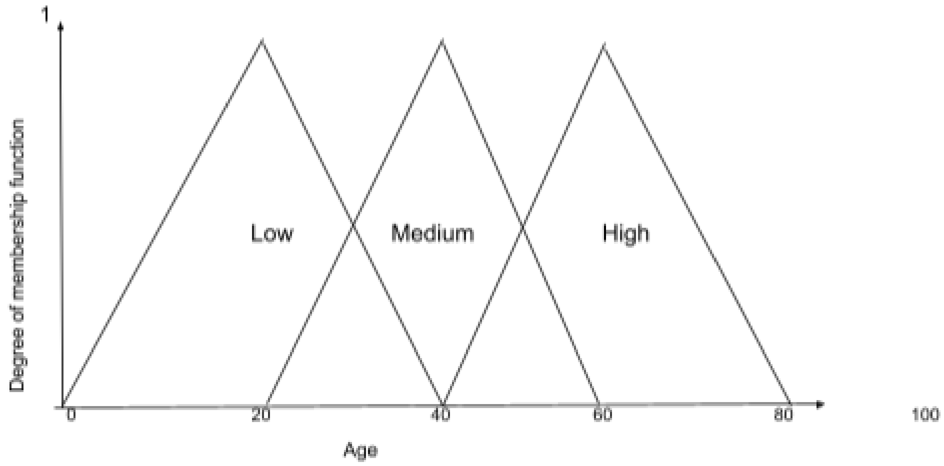

Fig. 3.5. Membership function - Age

Fuzzy membership functions of x = 75 for the fuzzy set H-High

Delta 1 = 75 - 40 = 25
Delta 2 = 80 - 75 = 5
Slope 1 = 1/20 = 0.05
Slope 2 = 1/20 = 0.05

$\mu_H(x)$ = min(25 * 0.05, 5 * 0.05, 1)
= min(1.25, 0.25, 1)
= 0.25

Fuzzy membership functions of x = 75 for the fuzzy set M - Medium.

Delta 1 = 75 - 20 = 55
Delta 2 = 60 - 75 = -15
Slope 1 = 1/20 = 0.05
Slope 2 = 1/20 = 0.05

$\mu_M(x)$ = 0

Fuzzy membership functions of x = 75 for the fuzzy set L - Low

Delta 1 = 75 - 0 = 75
Delta 2 = 40 - 75 = -35
Slope 1 = 1/20 = 0.05
Slope 2 = 1/20 = 0.05

$\mu_L(x)$ =0

The computation of the fuzzy membership values for the Grade (x = 65), the qualifying fuzzy sets are shown in the figure 3.6.

Fuzzy membership functions of x = 65 for the fuzzy set H - High

Delta 1 = 65 - 40 = 25
Delta 2 = 80 - 65 = 15
Slope 1 = 1/20 = 0.05
Slope 2 = 1/20 = 0.05

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 2, 2022, p. 2569 - 2576
https://publishoa.com
ISSN: 1309-3452

$\mu_H(x)$ = min(25 * 0.05, 15 * 0.05, 1)

= min(1.25, 0.75, 1) = 0.75

Fuzzy membership functions of x = 65 for the fuzzy set M - Medium

Delta 1 = 65 - 20 = 45
Delta 2 = 60 - 65 = -5
Slope 1 = 1/20 = 0.05
Slope 2 = 1/20 = 0.05

$\mu_M(x)$ = 0

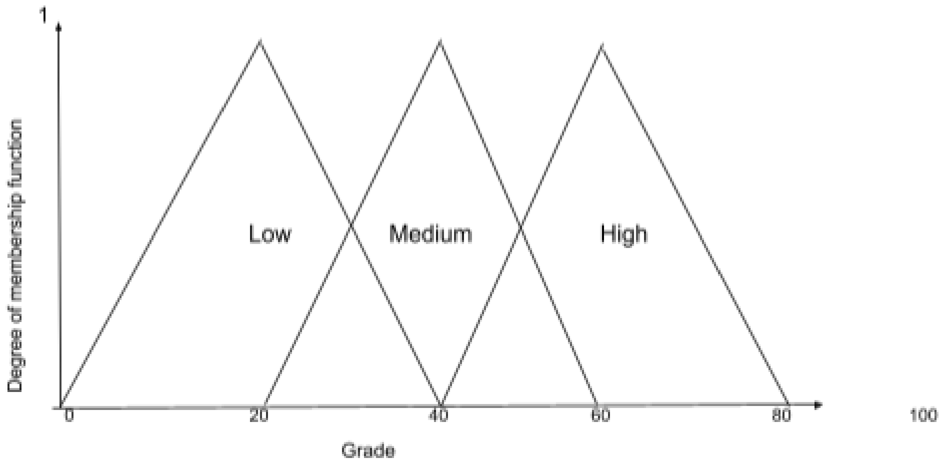

Fig. 3.6. Membership function - Grade

Fuzzy membership functions of x = 65 for the fuzzy set L - Low

Delta 1 = 65 - 0 = 65
Delta 2 = 40 - 65 = -25
Slope 1 = 1/20 = 0.05
Slope 2 = 1/20 = 0.05

$\mu_L(x)$ =0

For the Fuzzy rule base, the fuzzy membership values are

Rule 1 : min(0, 0) = 0
Rule 2 : min(0,0) = 0
Rule 3 : min(0, 0.75) = 0
Rule 4 : min(0, 0) = 0
Rule 5 : min(0,0) = 0
Rule 6 : min(0,0.7) = 0
Rule 7 : min(0.25, 0) = 0
Rule 8 : min(0.25,0) = 0
Rule 9 : min(0.25,0.75) = 0.25

That is the output of rule 9.

That is If Grade is High and the Age is High Then the Risk is High.

4. Conclusion

In this paper the general description and requirements for designing and creating a decision support system based on convolution neural network and fuzzy logic are presented, the combined model first classifies the input image whether it has tumor or not, if yes the fuzzy inference systems further categories to the risk of tumor based on the age and grade of crisp inputs. This work could be further extended to a hybrid-model where the output of a neural system to the input of a fuzzy system.

Reference

1. Kimberly D. Miller, Quinn T. Ostrom, Carol Kruchko, Nirav Patil,Tarik Tihan, Gino Cioffi, Hannah E. Fuchs, Kristin A. Waite, Ahmedin Jemal, Rebecca L. Siegel, Jill S. Barnholtz-Sloan, "Brain and other central nervous system tumor statistics", 2021.
2. Y. Zhang, A. Li, C. Peng and M.Wang, "Improve Glioblastoma Multiforme Prognosis Prediction by Using Feature Selection and Multiple Kernel Learning," IEEE/ACM Transactions on computational Biology and Bioinformatics, vol. 13, no. 5, pp. 825-835, 1 2016.
3. "Tumor Types: Understanding Brain Tumors," National brain tumor society, 2018.
4. Badža MM, Barjaktarović MC (2020) Classification of brain tumors from MRI images using a convolutional neural network. Appl Sci 10(6):1–13. https://doi.org/10.3390/app10061999
5. Sakshi Indoliaa, Anil Kumar Goswamib, S. P. Mishra, Pooja Asopaa, "Conceptual Understanding of Convolutional Neural Network- A Deep Learning Approach", 132 (2018) 679–688
6. Rikiya Yamashita, Mizuho Nishio, Richard Kinh Gian Do & Kaori Togashi, "Convolutional neural networks: an overview and application in radiology", 9, pages 611–629 (2018)
7. A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," in NIPS,2012.
8. S.Rajasekaran and G. A. Vijayalakshmi Pai. Neural Networks, Fuzzy logic, And Genetic Algorithms: Synthesis and Applications. (December 2009)187-221.
9. Poonam Gupta. Application of Fuzzy Logic in Daily Life. International Journal of Advanced Research in Computer Science. 2017; 8(5):1795-1800.
10. Hind R. Mohammed, Zahir M. Hussain, "Hybrid Mamdani Fuzzy Rules and Convolutional Neural Networks for Analysis and Identification of Animal Images", Computation 2021, 9,35. https://doi.org/10.3390/ computation9030035
11. Nguyen, TL, Kavuri, S, and Lee, M (2019). A multimodal convolutional neuro-fuzzy network for emotion understanding of movie clips. Neural Networks. 118, 208-219. https://doi.org/10.1016/j.neunet.2019.06.010
12. An, J, Fu, L, Hu, M, Chen, W, and Zhan, J (2019). A novel fuzzy-based convolutional neural network method to traffic flow prediction with uncertain traffic accident information. IEEE Access. 7, 20708-20722. https://doi.org/10.1109/ACCESS.2019.2896913
13. Umoh, U, Umoeka, I, Ntekop, M, and Babalola, E (2018). Interval type-2 fuzzy neural networks for short-term electric load forecasting: a comparative study. International Journal on Soft Computing. 9, 1-20. https://doi.org/10.5121/ijsc.2018.9101