# NATIONAL INSTITUTE OF TECHNOLOGY TIRUCHIRAPALLI

# CSPE – 72
# DEEP LEARNING TECHNIQUES
# PROJECT REPORT

Image Classification using Fuzzy Convolutional Neural Network

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# 1 Introduction

Medical imaging is essential in modern healthcare, supporting diagnosis, monitoring, and treatment planning for numerous diseases. Magnetic Resonance Imaging (MRI), in particular, is highly effective for visualizing soft tissues and plays a crucial role in detecting brain tumors - abnormal and potentially fatal growths within the skull. However, manual MRI interpretation is time-consuming, dependent on expert radiologists, and prone to variability, especially due to subtle similarities between tumor and non-tumor tissues.

To overcome these challenges, Computer-Aided Diagnosis (CAD) systems using Artificial Intelligence (AI) have gained prominence. Deep Learning (DL), especially Convolutional Neural Networks (CNNs), has proven highly successful in image-based medical diagnosis. Yet, conventional CNNs may struggle to handle uncertainty and ambiguity inherent in medical images. Fuzzy logic, which models vagueness and imprecision through degrees of membership, offers a complementary solution. Integrating it with CNNs gives rise to Fuzzy Convolutional Neural Networks (F-CNNs), which combine CNNs' feature extraction power with fuzzy reasoning to improve robustness and interpretability.

Motivated by recent studies highlighting the potential of fuzziness in medical imaging, this project implements and evaluates an F-CNN model for a classification task. A custom fuzzy layer based on Gaussian membership functions is integrated into a standard CNN architecture, and its performance is compared against a baseline CNN to assess the benefits of fuzzy logic in enhancing classification accuracy and reliability.

# 2 Literature Review

Recent studies have increasingly focused on combining fuzzy logic with Convolutional Neural Networks (CNNs) to improve performance in complex classification tasks where uncertainty and ambiguity are significant. Traditional CNNs excel at hierarchical feature extraction but often struggle with uncertain or overlapping class boundaries - a common issue in medical imaging. Fuzzy logic, on the other hand, provides a mathematical framework to handle such imprecision through the use of membership functions and linguistic reasoning. Integrating these two approaches has led to the development of hybrid models such as Fuzzy Convolutional Neural Networks (F-CNNs), which aim to improve both interpretability and robustness.

Korshunova (2018) introduced one of the early implementations of a Convolutional Fuzzy Neural Network (CFNN) for general image classification. The proposed model combined a standard convolutional feature extractor with a fuzzy self-organization layer that performed unsupervised fuzzy clustering on extracted features. This layer assigned membership values representing the degree of association between feature vectors and fuzzy clusters, thereby incorporating uncertainty directly into the network's reasoning process. The model was evaluated on the Dogs vs. Cats dataset, consisting of 25,000 training and 12,500 test images. Results showed a significant accuracy improvement—from 55.6% to 70.8% after fine-tuning—compared to a conventional CNN, highlighting the advantage of integrating fuzzy logic for handling ambiguous data.

Extending this idea to the medical domain, Mahdi, Shujaa, and Zghair (2023) applied an F-CNN architecture to the classification of brain tumor MRI images. Using the publicly available Brain Tumor MRI Dataset, which includes 7,022 images categorized as glioma, meningioma, pituitary tumor, and non-tumor, their approach combined convolutional, pooling, and dense layers with a fuzzy inference layer placed between fully connected layers. The model was trained end-to-end using the Adam optimizer and categorical cross-entropy loss for 500 epochs. Pre-processing involved resizing images to 128×128, rescaling, and applying random augmentations such as rotation and flipping. The proposed F-CNN achieved an impressive 99.31% validation accuracy with relatively low computational cost, demonstrating that fuzzy logic integration can enhance CNN-based medical image classification systems.

Together, these studies provide compelling evidence for the efficacy of combining fuzzy logic and CNNs. They establish a strong foundation for the present work, which applies a similar hybrid architecture to brain tumor MRI classification to evaluate the impact of fuzzy layers on improving diagnostic accuracy and robustness.

# 3. Proposed Work

This section presents the overall methodology adopted for developing and evaluating the proposed Fuzzy Convolutional Neural Network (FCNN). It outlines the architectures of both the baseline CNN and the proposed FCNN, training procedure, and comparative performance results, and dataset.

**Standard CNN Architecture**

The baseline model follows a conventional Convolutional Neural Network (CNN) design commonly used for image classification tasks. The network consists of multiple convolutional layers for feature extraction, each followed by batch normalization, ReLU activation, max pooling, and dropout layers to ensure stability and prevent overfitting.

After the convolutional stages, the extracted features are flattened and passed through two fully connected layers with ReLU activation. The final layer employs a softmax activation function to classify the MRI scans into the four categories. This baseline model serves as the reference architecture to measure the effectiveness of the proposed fuzzy extension.

| Layer Type | Output Shape / Features | Details |
|---|---|---|
| Input Image | (3, 224, 224) | 3-channel RGB image of size 224x224 |
| Conv Block 1 | (32, 112, 112) | 2x Conv(32 filters), MaxPool(2,2), Dropout |

| | | |
|---|---|---|
| Conv Block 2 | (64, 56, 56) | 2x Conv(64 filters), MaxPool(2,2), Dropout |
| Conv Block 3 | (128, 28, 28) | 2x Conv(128 filters), MaxPool(2,2), Dropout |
| Conv Block 4 | (256, 14, 14) | 2x Conv(256 filters), MaxPool(2,2), Dropout |
| Flatten | 50176 | Flattens the final feature map |
| FC1 (Dense) | 512 | Linear layer + BatchNorm + ReLU + Dropout |
| FC2 (Dense) | 256 | Linear layer + BatchNorm + ReLU + Dropout |
| Output Layer | 4 | Final Linear Classification Layer |

*Table 1 : Architecture of the Standard CNN*

**Fuzzy Convolutional Neural Network (FCNN)**

To enhance the model's ability to handle uncertainty in MRI features, we propose a method to enhance the standard CNN architecture with a fuzzy logic layer, forming the Fuzzy CNN (FCNN). The convolutional and initial fully connected layers remain the same as the baseline CNN, ensuring a consistent feature extraction process.

The novelty lies in the integration of a fuzzy inference mechanism after the first fully connected layer. The fuzzy layer employs Gaussian membership functions to model the degree of belonging of input features to different fuzzy sets. Each membership function has learnable parameters that adapt during training, allowing the network to dynamically capture uncertainty and imprecision in the extracted features.

The membership degree for each rule is computed as:

$$\mu_i(x) = \exp\left(-\frac{(x - c_i)^2}{2\sigma_i^2}\right)$$

The output of this fuzzy layer is concatenated with the original feature representation, enabling the model to incorporate both crisp and fuzzy information before final classification. The following fully connected and output layers then perform the final prediction based on these enriched representations.

| Layer Type | Output Shape / Features | Details |
|---|---|---|
| Input Image | (3, 224, 224) | 3-channel RGB image of size 224x224 |

| | | |
|---|---|---|
| Conv Block 1 | (32, 112, 112) | 2x Conv(32 filters), MaxPool(2,2), Dropout |
| Conv Block 2 | (64, 56, 56) | 2x Conv(64 filters), MaxPool(2,2), Dropout |
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| Conv Block 4 | (256, 14, 14) | 2x Conv(256 filters), MaxPool(2,2), Dropout |
| Flatten | 50176 | Flattens the final feature map |
| FC1 (Dense) | 512 | Linear layer + BatchNorm + ReLU + Dropout |
| **Fuzzy Layer** | **5** | **Gaussian membership functions on 512 features** |
| Concatenation | 517 | Combines outputs of FC1 (512) and Fuzzy Layer (5) |
| FC2 (Dense) | 256 | Linear layer + BatchNorm + ReLU + Dropout |
| Output Layer | 4 | Final Linear Classification Layer |

*Table 2 : Architecture of the FCNN*

**Training Process**

Both models — CNN and FCNN — were trained using the Adam optimizer and cross-entropy loss function. Training was conducted for multiple epochs with GPU acceleration to ensure efficient computation. The learning rate, batch size, and regularization parameters were kept identical for both models to ensure a fair comparison.

**Dataset Description**

The Brain Tumor MRI Dataset from Kaggle was utilized in this study. It contains over seven thousand MRI scans categorized into four classes — glioma, meningioma, pituitary, and no tumor. The dataset was divided into training and testing subsets to ensure fair model evaluation. Each image was resized to a fixed dimension and normalized to ensure consistency in input features. Data augmentation techniques, including random rotations and horizontal flips, were applied to the training set to improve generalization and prevent overfitting. The testing set remained unaltered to maintain evaluation integrity.

# 4. Results

This section presents a comparative performance evaluation of the proposed Fuzzy Convolutional Neural Network (FCNN) and the standard CNN baseline on the brain tumor dataset. To examine learning behavior and convergence, both models were trained for 20 and 50 epochs.

During the 50-epoch training run, the FCNN consistently outperformed the standard CNN in terms of accuracy. As shown in the training accuracy curve (Figure 1), the FCNN achieved higher accuracy from the initial epochs and maintained this advantage throughout training, attaining a final training accuracy of 97.86%. In contrast, the CNN exhibited a similar learning trend but consistently lagged behind, converging at 92.85%.

Although both models exhibited nearly identical training loss curves, the FCNN achieved higher accuracy, implying that it was more effective at making correct classifications even when overall loss levels were similar. This observation suggests that the integration of fuzzy logic improved the network's decision-making ability by better handling uncertainty in the learned representations.

When evaluated on the unseen test set, the proposed FCNN achieved a test accuracy of 98.86%, outperforming the baseline CNN, which attained 94.32%. This 4.54% improvement demonstrates the FCNN's superior generalization capability. The results confirm that incorporating fuzzy logic enables the network to better capture ambiguous or overlapping features in images, leading to more robust and reliable classification.

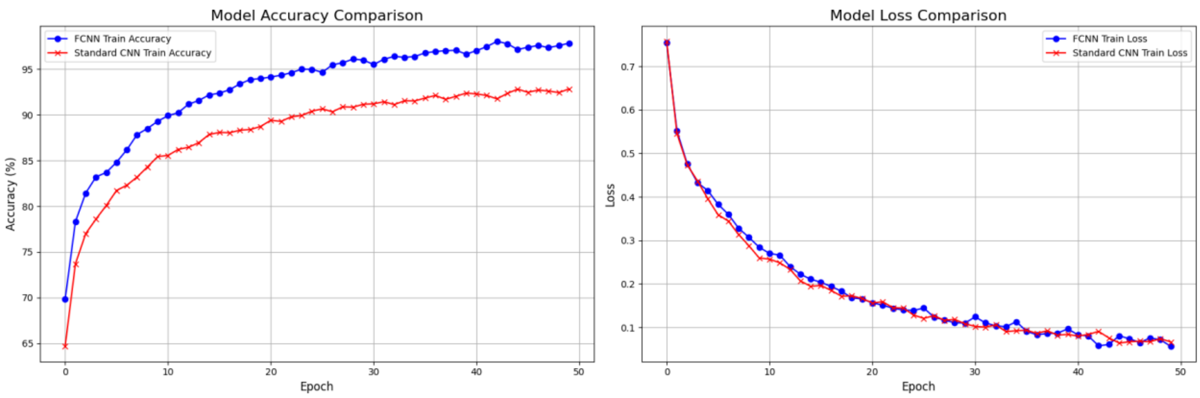


*Fig 1:Comparison Training CNN vs FCNN*

# 5. Conclusion

This research presented a comparative study of a conventional Convolutional Neural Network (CNN) and a proposed Fuzzy Convolutional Neural Network (FCNN) for brain tumor classification using MRI images. The FCNN architecture integrated fuzzy logic principles into the convolutional learning process, enabling the model to better capture uncertainty and ambiguity inherent in medical image features. Experimental evaluation demonstrated that the FCNN achieved a test accuracy of 98.86%, outperforming the standard CNN by 4.54%. The results confirmed that the introduction of fuzzy logic enhanced both the learning stability and decision reliability of the model without increasing architectural complexity. Overall, the proposed FCNN provides a robust framework that bridges the interpretability of fuzzy systems with the representational strength of deep neural networks, thereby contributing to the development of hybrid intelligent learning architectures.

# 6. Future Scope

The potential of the FCNN extends well beyond medical image analysis. Future research could explore integrating fuzzy modules within more advanced deep learning architectures such as Vision Transformers (ViTs), Graph Neural Networks (GNNs), or hybrid CNN–Transformer pipelines to improve uncertainty handling and adaptive reasoning. The fuzzy logic layer can be redefined as a learnable attention mechanism, allowing dynamic rule formation based on feature distributions rather than fixed membership functions. Moreover, extending the FCNN to unsupervised or self-supervised learning contexts could enhance its generalization to limited-label or noisy datasets. Further studies may also investigate optimization strategies for the fuzzy parameters to reduce computational overhead and improve scalability across larger and more complex datasets.