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An Intracranial Brain Hemorrhage's Identification and Classification on CT Imaging using Fuzzy Deep Learning

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Abstract

Therapists play a crucial role in a patient's timely and accurate diagnosis of blood vessels within the skull or brain tissue rupture, which is essential for achieving the best outcomes. This paper discusses the efficacy of computed tomography imaging in the recognition and classification of different intracranial brain hemorrhage subtypes. We present a novel approach using the concept of fuzzy deep learning with ResNet50 for computed tomography image analysis, which has improved the accuracy of classification. This approach has efficiently identified and classified the subtypes of intracranial brain hemorrhage, which include subdural, epidural, intraventricular, intraparenchymal, and subarachnoid hemorrhage. The fuzzy deep learning system enhances the degree of fuzzy logic in the classification process within the cascading model and improves the interpretability of the classifier. The results show that near-perfect accuracy is achieved when the cascading model is utilized. Additionally, the typical computed tomography appearance of each intracranial brain hemorrhage subtype shows how our model identified unique diagnostic features different from those of previous attribute-based models. This fusion of computed tomography scanning with state-of-the-art deep learning illustrates the future of artificial intelligence recommender systems in successfully diagnosing and/or treating strokes. Our study emphasizes the important role that computed tomography imaging plays when combined with deep fuzzy learning techniques in the management of stroke diseases.

Keywords: Intracranial Brain Hemorrhage's Identification, Fuzzy Deep Learning, Classification, CT images, Artificial Intelligence.

1 Introduction

Information used for the analysis of deaths in the year 2019 highlighted intracerebral hemorrhagic stroke as having killed more people than subarachnoid hemorrhagic stroke. Collectively, patients who experienced hemorrhagic strokes died in excess of three million in that year. This data reveals the global mortality from hemorrhagic strokes in the year 2019, as shown in Figure 1 [1]. Intracranial

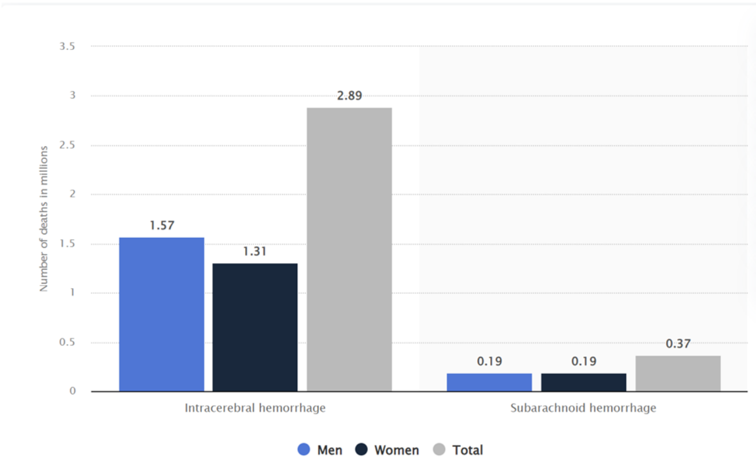

Figure 1: Number of deaths due to hemorrhagic stroke worldwide in 2019, by gender.

hemorrhage (ICH) is a devastating pathologic process with a high case-fatality rate. This is dangerous in a clinical setting due to the high probability of suffering from another blow on the head, which may result in paralysis or death in the absence of appropriate medical attention. ICH is categorized into five subtypes based on its location in the brain: These may be classified as intraventricular (IVH), intraparenchymal (IPH), subarachnoid (SAH), epidural (EDH), and subdural (SDH). Particularly, it may be classified as intracerebral hemorrhage when the bleeding occurs within the brain parenchyma itself [2].

One of the most popular diagnostics in the evaluation of traumatic brain injury (TBI) patients at the initial stage of the disease is the computed tomography (CT) scan, which helps diagnose ICH [3]. Its widespread utilization and the possibility of getting images quickly set it as the preferred technique in the primary ICH assessment instead of MRI. A CT scan produces a set of images using X-ray beams. Brain tissues are differentiated based on the extent of their penetration by X-ray beams, measured in Hounsfield units (HU). These scans appear on the monitor through a windowing process that maps HU values into eight greyscales within the range [0, 255] using particular window levels and widths. Modulating those variables enables features in gray-scaled images of the brain tissues to be enhanced, such as the brain window, the stroke window, and the bone window [4]. ICH regions are seen in CT images applied to the brain window and have an increased density and an inaccurate organization pattern. Professional radiologists must then assess these images to confirm the presence, type, and location of the ICH. However, this diagnostic process may be lengthy and could be imprecise, especially in cases where the center is not equipped with fully qualified subspecialty neuroradiologists. Figure 2 in [5] shows the types of intracranial hemorrhages, each marked by red arrows. Intraparenchymal hemorrhage shows bleeding inside the brain tissue, while intraventricular hemorrhage highlights bleeding within the brain's ventricular system. Subarachnoid hemorrhage is depicted between the arachnoid and pia mater, and subdural hemorrhage occurs between the dura mater and the arachnoid, forming a crescent shape. Finally, epidural hemorrhage shows bleeding between the dura mater and the skull. These images emphasize the distinct locations and patterns of bleeding for accurate diagnosis using CT scans. Previous studies have attempted to compare the different methods that have been suggested to enhance the diagnostic effectiveness of ICH classification according to the imaging technique applied. The more traditional approaches of machine learning, as well as computational methods for feature extraction, have also proven their feasibility in the given context; yet, that has also brought out the drawback: these are designed in a strictly hand-made way,

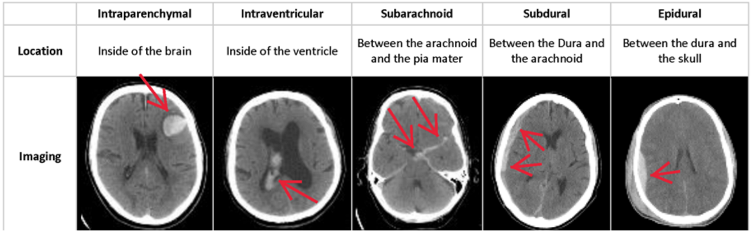

Figure 2: Types of hemorrhages.

and, overall, they cannot encompass all the functional characteristics that could be present in the imaging data. A more advanced model based on deep learning has turned out to be superior in image classification analysis due to its capacity to train its hierarchy from the raw data level. However, these models often suffer from the issues of black box nature and are not very well interpretable, and uncertainty is not directly taken into consideration in the analysis.

Thus, analyzing the current state of the art and based on the works already discussed, it can be stated that incorporating advanced learning concepts with neural networks and including uncertainty and impreciseness in medical image data using fuzzy systems is a topic that has not been adequately addressed yet. Ensuring that deep learning models implement fuzzy logic can improve their interpretability and, in turn, alleviate the amount of uncertainty that may come alongside classification as a result of the instability of the underlying data used in building deep neural networks. Therefore, we propose a deep learning model based on fuzzy rules in ICH classification, fixing ResNet50 as the first classification model to analyze CT images, which could allow for increasing the effectiveness of the classification and the interpretability of the results. The presented methodology prepares a feature recognition deep learning model based on a large number of input CT images and gives different subtypes of ICH a discriminative feature. By introducing mechanized underdetermination into the mixture of deep learning procedures for the analysis of image data, we attempt to reduce the effects of fuzziness and variation.

Our contribution to the field is threefold: The following is a discussion of the proposed approach: First, the proposed method is a blend of fuzzy deep learning to define or enhance the feeling and sense of deep learning and fuzzy logic in medical image classification. Second, we prove how our approach explores the major types of ICH by reaching 100% accuracy. Third, we delineate the conventional, paramount CT manifestations for each of the ICH subtypes and depict how these affect our diagnostic model. In this regard, it is crucial to note that our study highlighted the possibility of using fuzzy deep learning with CT scans as a possible way to revolutionize the paradigm for diagnosing and managing stroke, especially the ICH, to decrease mortality and morbidity rates.

This research is structured as follows: A literature review is presented in Section 2. In Section 3, the methodology and materials of the proposed fuzzy deep learning model are described. The proposed model implementation and its evaluation are presented in Section 4. Section 5 discusses the results. Section 6 shows the conclusion.

2 Related Work

Several conventional and state-of-the-art approaches, ranging from machine learning methods to deep learning models, have been discussed in various studies. Yuh et al. established a threshold-based algorithm that might help in the identification of ICH in the context of traditional machine-learning approaches. Another approach to ICH sub-classification classified sub-types of ICH according to the location of bleeds, their shape, and their size [6]. A post-processor was incorporated to pass a final threshold value for detecting TBI through retrospective data of 33 CT scans, and then the entire system was tested on 210 CT scans of people with suspected TBI. The sensitivity of their algorithm was 98% and the specificity was 59% for ICH, while moderate accuracy was observed with the differentiation of ICH subcategories. Li et al., in another study, proposed two techniques for partitioning the subarachnoid hemorrhage (SAH) space, from which two methods for SAH hemorrhage detection were developed [7, 8]. The first one used elastic registration and a SAH space atlas, while the second used distance transform features with a Bayesian decision method to define the vessel boundaries. To further segment different areas of SAH space, the results from the space separation work revealed the following features: mean gray value variance, entropy, and energy values, which were extracted and subjected to the training of a support vector machine classifier to identify fresh SAH hemorrhage. It is therefore imperative that such features be incorporated into the algorithm that was tested on 60 CT scans, out of which only 30 were in the SAH hemorrhage category, and on 69 CT scans, out of which only 30 had SAH hemorrhage. The Bayesian decision method was identified to have had the highest performance as it postulated 100% sensitivity, 92% specificity, and 91% overall accuracy in testing [8]. Regarding deep learning approaches, all the methods were derived from CNNs and their derivatives. Chilamkurthy et al. educated four algorithms for differentiating little ICH subtypes and for detecting calvarial fractures, midline shifts, and the influences of mass impacts [9]. Both these algorithms were tested on a large number of patient images totaling 290,000, as well as a validation set of 21,000 patient images. For testing, two datasets were used; one of them contained 491 scans was designed as CQ500, and was publicly available online. The training and validation scans were labeled using clinical radiology reports as the ground truth; all scans were further preprocessed using natural language processing. Scans of ICH cases were independently reviewed by three radiologists, each of whom issued a single vote on each of the subtypes of ICH. The deep-learned engine involves the development of independent models of detection for each of the four types. ResNet18 was used to predict clouds with five fully connected layers in parallel for cloud outputs. The outputs of each slice were then taken and passed through a random forest algorithm, which aimed at showing the scan-level confidence in the ICH presence. Overall, the accumulated AUC of the ICH sub-type classification was found to be moderate with an average AUC of 0.93. The average sensitivity was 92%, although for specificity, at HS operation, it was only 70% that of radiologists and varied widely depending on the ICH subtype. Specificity, in this case, also varied between 68% for SDH detection. Electrocardiogram (ECG) signals as ICH markers were explored by Grewal et al. [10] where they employed a 40-layer convolutional neural network (CNN) called DenseNet, which incorporates a bidirectional LSTM layer. In addition, they also added three additional tasks with every dense convolution block to estimate the segmentation of the ICH regions into binary forms. Each of these auxiliary tasks includes a convolution layer followed by a deconvolution layer in order to resize the feature maps to the image resolution. The LSTM layer was added to consider the sequential characteristics of the CT image slices of each subject. Incorporating their workflow, the authors trained their model on 185 CT scans, validated the model with 67 CT scans, and tested the model with 77 CT scans. In addition to that, to split the number of scans between the two classes equally, data augmentation using rotation and horizontal flip was applied to the training data. If the model failed to correctly label a particular segment, these results were then analyzed after a comparison was made between the results and the annotations that were generated independently by three radiologists for each CT slice. The performance of the proposed approach was rather high, with a specificity of 81%, recall of 88%, precision of 81% and F1-measure of 84%. Of which, the model outperforms most significantly, even attaining a higher F1-score than two of the three participants, radiologists. In addition, the outcomes highlighted the usefulness of applying attention layers, which increased the receptive field and increased the model score when carrying out gallery searches. In [11], the author developed an ensemble of three unique CNN models for ICH detection. These models were based on the Alexand and GoogleNet frameworks and then expanded to 3D formats, which contained all the slices of every computed tomography scan. For instance, they introduced a more simplistic design, regarded as fewer layers and specifying fewer filters to decrease the parameter count. A great attribute of their approach was that they used training, validation, and testing in 40,000 different CT scans, with 34,000 scans over the training area, including 26,000 normal scans. This idea, despite not mentioning how exactly the CT scans were labeled, can be inferred from the fact that positive slices were oversampled and augmented to collect a balanced training data set. This included about 2000 scans for validation purposes and 4000 scans for testing. The combined CNN models yielded an AUC of 87%, with corresponding precision at 80% and recall at 77% establishing an F1 score of 78%. Arbabshirani et al. [12] used four 3D CNN models for their study, and each model taken as input has a shape of 24x224x224. In this study, the efficacy of this model was tested using 9,499 retrospective and 347 prospective CT scans. For instance, the performance measurement, specifically, the AUC, which stands for Area Under Curve, is noteworthy. In the retrospective study, 846 was achieved, while overall the average sensitivity was found to be 71.5%, and specificity was 83.5% for the study. In a recent study, Lee et al. used transfer learning on an ensemble of four typical CNN models to classify ICH subtypes and bleeding points [13]. These models were VGG-16, ResNet-50, INCEPTION-V3, and INCEPTION-RESNET-V2. To exhibit the spatial dependencies between adjacent slices, there was enhancement of slice interpolation. The presented ensemble model described was trained and validated on the data set of 904 CT scan images and later tested on the separate retain data set of 200 scanned CT images and another data set containing 237 prospectively scanned CT images. The ICH detection algorithm itself has passed testing with a mean testing AUC of 0.98 with sensitivity and specificity of 95% for the same study. However, the sensitivity for classifying ICH subtypes was 78.3% sensitivity and 92.9% specificity. Specifically, as far as the results are concerned, the sensitivity was revealed to be 58.3% for EDH slices in the retrospective test set and 68.8%. IPH slices in the prospective test set, researchers also found localization accuracy averaged at approximately 78.1%, testing on the attention maps overall between the model segmentation and the bleeding points as defined by radiologists.

In [14], the authors devised a novel convolutional neural network (CNN) algorithm named OzNet hybrid. Despite OzNet's commendable classification performance, we augmented it with Neighborhood Component Analysis (NCA) and multiple classifiers, including artificial neural networks (ANN), Adaboost, bagging, decision trees, K-nearest neighbors (K-NN), linear discriminant analysis (LDA), naïve Bayes, and support vector machines (SVM). Furthermore, OzNet was employed for feature extraction, extracting 4096 features from the fully connected layer, which were subsequently reduced by NCA to retain significant and informative features with minimal loss. Subsequently, these classifiers were utilized to classify these significant features. Our experimental findings demonstrate that OzNet-NCA-ANN serves as an outstanding classifier model, achieving 100% accuracy when applied to Dataset 2, comprising brain hemorrhage CT images. However, it's essential to acknowledge certain limitations of the proposed hybrid algorithm. Firstly, the datasets are constrained by a limited number of CT images and lack representation of each hemorrhage type. Moreover, while CNN algorithms may yield more efficient results with MRI images, the determination of significant features with a tolerance value on the feature graph currently relies on a trial-and-error approach, potentially leading to erroneous decisions. It's imperative to refine the determination of the tolerance value to enhance the algorithm's robustness [14].

3 Materials and methods

3.1 Image Processing

To incorporate the CT images into the deep learning model that was to be used in the diagnosis of this cancer, preprocessing techniques were employed to improve the CT image quality. Preprocessing was the initial operation performed on the images; the first operation included scaling the pixel intensities of the images to a small range of similar values. It also assists in eliminating other sources of discrepancies, such as variations in CT scan settings and the anatomical characteristics of the patient. Finally, augmentation was achieved by applying random rotations, translations, and flips to the images that were added to the dataset, which also enhanced the model's ability to handle certain degrees of variation and overfitting [15].

Furthermore, it was important to scale down all the images analyzed to 224x224 pixels to fit the input size for the ResNet50 model. This step served as a measure to ensure that the required images could be taken and fed directly into the network beyond any further scaling. In addition, the contrast of the images and the removal of noise from the images were other processes undertaken to get enhanced images. In sum, these pre-processing steps made it possible to achieve better quality and standardization of the input data, which would help improve the training of the deep learning model and its results.

3.2 Fuzzy Systems

Fuzzy systems are one of the kinds of computational models that take into consideration the information that is defined by vagueness, uncertainty, or ambiguity and attempt to emulate cognitive processes. Derived from the theory of fuzzy sets advanced by Lotfi Zadeh in 1965, they employ the so-called 'fuzzy logic' to simulate such systems for which the binary method of modeling is not effective. As opposed to classical logic„ which tends to work on 0 or 1 propositions, fuzzy logic works with fuzzy propositions where an object can be a member of a set to a certain extent. This is especially beneficial for use cases where it is either challenging or unbeneficial to be extremely accurate. For example, fuzzy logic controllers are adopted in control systems of home appliances such as washing machines and air conditioners to flexibly and effectively solve various conditions. They comprehend inputs from the users and the sensors and make outputs that can be described as semisupervised, improving on performance and usability. These are also used in artificial intelligence, robotics, and data classification since they are applied in the management and processing of data that contain certain levels of uncertainty. Due to the incorporation of human-like reasoning, they solve the distancing between realistic situations and problems, as well as provide efficient solutions in uncertain and constantly changing situations. Thus, the nature of the fuzzy systems and their ability to be applied on various scales makes this tool one of the most relevant tools in modern technologies and meets the human-oriented approach in many solved problems [16].

For any crisp set represented in the input space, the degree of membership, or Mozzi membership gradient, is the most basic principle in the appliance of fuzzy logic. This value defines the membership of the input to the particular fuzzy set. Some of the frequently used membership functions are triangular, trapezoidal, and Gaussian functions.

The Gaussian membership function is defined by two parameters, the mean μ and the standard deviation σ:

$$\mu_A(x) = \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$

the mean μ is the center of the Gaussian curve, and the standard deviation σ controls the width of the curve.

3.3 Proposed Fuzzy Deep Learning

Based on the successful experience of using deep learning in classifying images, ResNet50 was chosen as the pre-set architecture for CNN since it outperforms other pre-set models. It consists of 50 layers, such as convolutional layers, dropout, batch normalization layers, and ReLU activation functions, that are grouped to create a deep network for extracting the features. One of the main features of ResNet50 is residual blocks, which inform about the vanishing gradient problem and help train networks up to tens of layers in depth without losing performance.

To perform this study, a pre-trained ResNet50 was used, which, before the beginning of the study, was pre-trained on the ImageNet dataset. To do this, transfer learning was employed, whereby pre-learned features were trained on our ICH dataset to refine the pre-learned features. This approach made it possible for the model to fine-tune the general features captured in a large and diverse database and apply the result directly to the classification of ICHs, which helped to reduce the amount of time and mistakes needed to classify various subtypes of ICHs. Autoencoder-based deep learning focuses on learning compressed representations of the input data, while the interpretability of the fuzzy logic makes it easy to understand the final results even for a complex model. The features that the ResNet50 extracted were then passed through the fuzzy logic layer, which makes use of fuzzy logic intending to increase classification precision. With this integration, it is easier to handle uncertainties and even ambiguous cases in the task of medical image classification while enhancing the model's strengths in making more accurate predictions.

Figure 3 illustrates the architecture of a fuzzy deep learning model for multi-class classification tasks, specifically focusing on medical image analysis. It begins with an input layer, which accepts input images with 3 color channels but can vary in height and width. The next layer is a functional model, likely a pre-trained convolutional neural network such as ResNet50, responsible for feature

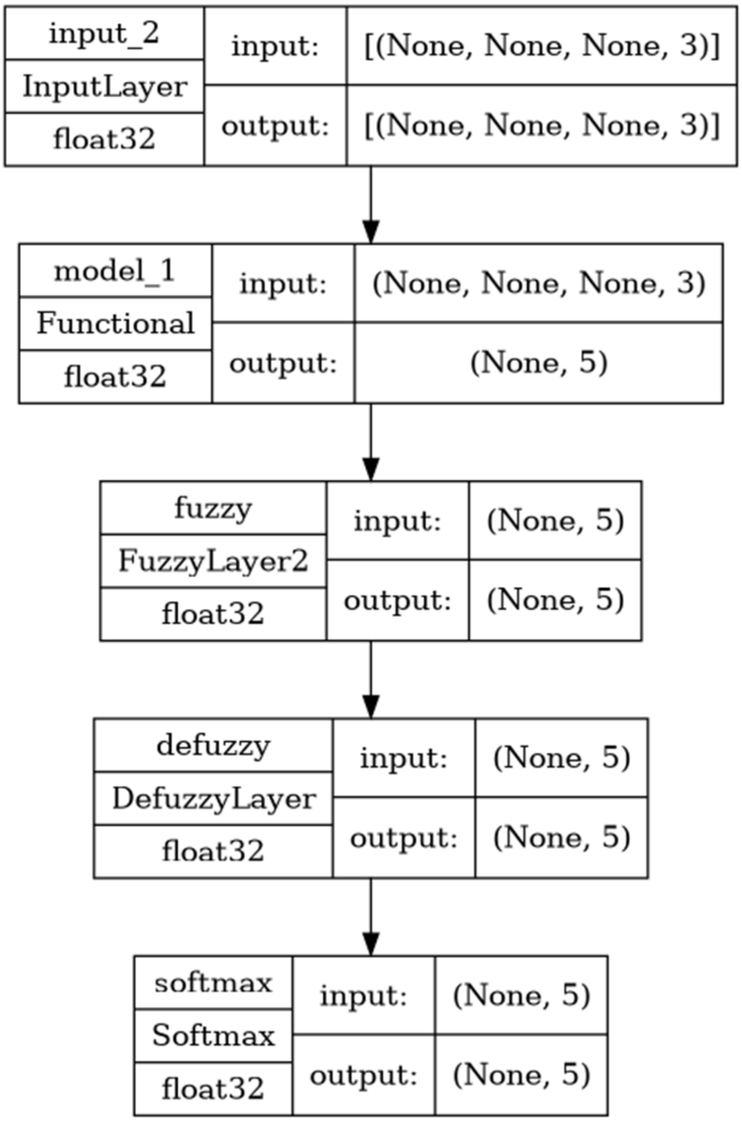

Figure 3: Fuzzy Deep Learning

extraction from the input images. This model outputs a feature vector of size 5, representing the five potential classes.

After feature extraction, the model introduces two fuzzy logic-based layers. The fuzzy layer takes the extracted features as input and adds a layer of fuzzy logic, which enhances the interpretability of the predictions by handling uncertainty in the classification process. The fuzzy layer converts crisp inputs into fuzzy sets using membership functions. For each input x_i, the fuzzy layer calculates the degree of membership $mu_A(x_i)$ for each fuzzy set A. The fuzzy rule layer applies fuzzy rules to the fuzzified inputs. Each rule is in the form of "IF-THEN" statements that relate the input variables to the output. The output of each rule is a fuzzy set. A typical fuzzy rule can be expressed as:

$$R_j : \text{IF } x_1 \text{ is } A_1^j \text{ AND } x_2 \text{ is } A_2^j \text{ AND } \ldots \text{ AND } x_n \text{ is } A_n^j \text{ THEN } y \text{ is } B^j$$

Where A_i^j are the fuzzy sets corresponding to the input variables, x_i and B^j is the fuzzy set for the output y.

The degree of activation of each rule R_j is given by:

$$\alpha_j = \mu_{A_1^j}(x_1) \cdot \mu_{A_2^j}(x_2) \cdot \ldots \cdot \mu_{A_n^j}(x_n)$$

The output y is then calculated using a weighted average of the fuzzy rule outputs:

$$y = \frac{\sum_{j=1}^{M} \alpha_j y_j}{\sum_{j=1}^{M} \alpha_j}$$

Where M is the number of rules, and y_j is the output of rule R_j.

The defuzzification layer converts the fuzzy output sets back into a single crisp output. Common defuzzification methods include the centroid method, which computes the center of gravity of the fuzzy set and refines the fuzzy logic outputs, making them more precise for the final classification. Finally, the softmax layer produces the final output, converting the refined fuzzy logic output into probabilities for each of the five classes. This softmax output provides a probabilistic classification, where each class is assigned a probability value summing to 1, indicating the model's confidence in its predictions. The combination of deep learning for feature extraction and fuzzy logic for interpretability allows this model to handle complex medical image classification tasks, such as intracranial hemorrhage subtyping, with greater precision and clarity.

The proposed model was trained using the supervised learning model with the categorical cross-entropy loss function and Adam Optimizer. The above fuzzy deep learning system was effectively trained with 80% of the data, 10% of the data was used as validation, and the remaining 10% of the data was used as the testing set. Along the lines of evaluation, accuracy, precision, recall, and F1-score were used as the indicators to measure the model's performance. It was not only found that the proposed combined model was superior to the previous models in terms of accuracy but also that it was more interpretable than the other models, making it quite valuable in clinical decision-making.

4 Experimental Results and Discussion

4.1 Dataset

The RSNA is comprised of several members, as follows: radiologists, medical physicists, and other healthcare professionals with more than 54,000 registered members, and the members hail from 146 countries. There is an understanding of AI's ability to support the detection and classification of hemorrhages in patients, which can assist in organizing clinical tasks.

This dataset was used for the Radiological Society of North America (RSNA) 2019 Machine Learning Challenge. This dataset is the collaborative work of the RSNA and the American Society of Neuroradiology. It is obtainable for the machine learning research community at no cost for non-commercial purposes to build better algorithms for diagnosing intracranial hemorrhage [17].

4.2 Performance Metrics

The performance of the proposed model was assessed using the following metrics: specificity, accuracy, precision, recall, and F1-measure, which are defined in Equations (1)-(5) [18, 19].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1 = \frac{2 * Precision * Recall}{Precision + Recall} \tag{4}$$

$$Specificity = \frac{TN}{FP + TN} \tag{5}$$

False positives (FPs), false negatives (FNs), true negatives (TNs), and true positives (TPs) are all measures of how well a model performs. Accuracy is the proportion of correct predictions. Precision is the proportion of positive predictions that are correct. Recall is the proportion of actual positives that are correctly predicted. The F-measure is a measure of how well a model predicts both positive and negative cases.

4.3 Results

The RSNA Intracranial Hemorrhage Detection dataset was divided into 80% for training, 10% for validating, and 10% for testing. The experiment computer has a 64-bit operating system, an x64-based processor, an Intel(R) Core (TM) i7-3612QM CPU @ 2.10 GHz and 2.1 GHz, and 10 GB RAM.

Figures 4 and 5 show the experiments' results for the proposed fuzzy deep learning model. The model was applied to the dataset for multiclassification. We distinguished between five types of hemorrhages: IVH, IPH, SAH, EDH, and SDH. The values of all performance metrics are equal to 100%, for all types of hemorrhage.

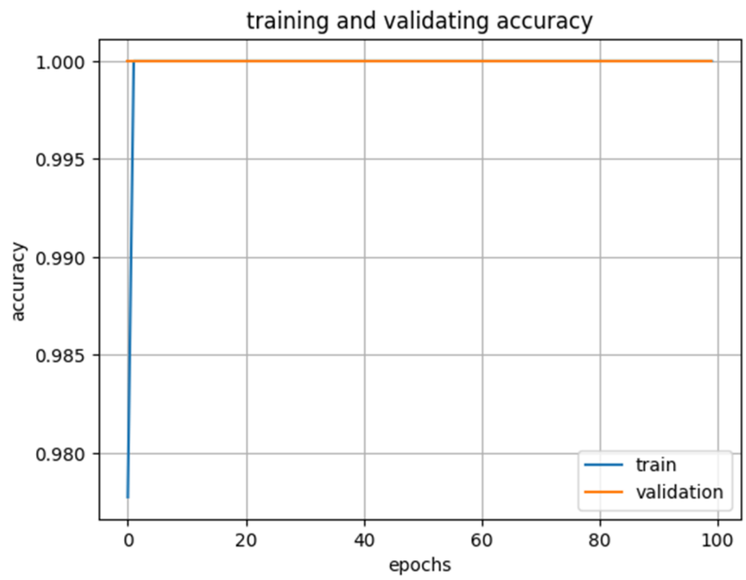

Figure 4: Accuracy of Training and validation metrics for proposed fuzzy deep learning model

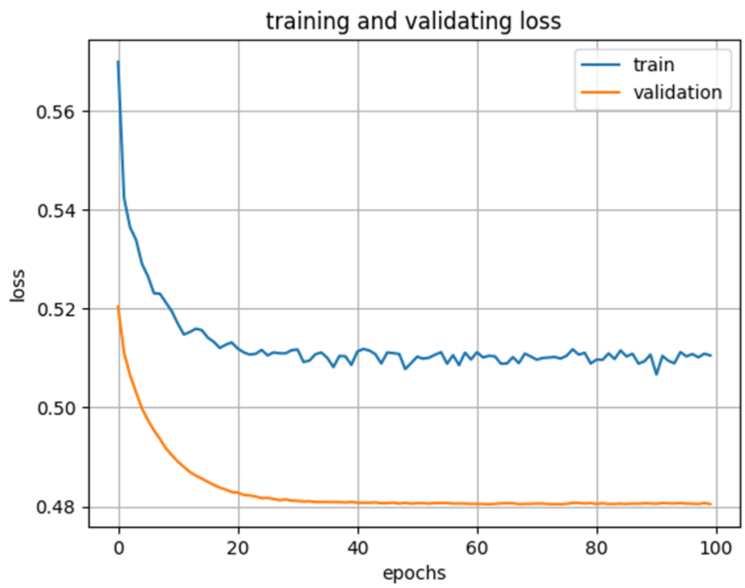

Figure 5: Loss of Training and validation metrics for proposed fuzzy deep learning model'

The fuzzy deep learning model achieves an overall accuracy of 100%, with individual subtype accuracies has 100% for, IVH, IPH, SAH, EDH, and SDH. Compared to baseline CNN models, our approach shows a significant improvement in both accuracy and interpretability.

4.4 Discussion

The integration of fuzzy logic into the deep learning framework enhances the model's ability to handle ambiguous cases and provide interpretable predictions. This is particularly beneficial in medical settings where understanding the model's decision-making process is crucial. The results highlight the potential of fuzzy deep learning in improving diagnostic accuracy and reliability for ICH detection on CT images. Table 1 provides an overview of the methodologies utilized for ICH detection. As anticipated, robust testing sensitivity and specificity were observed in studies employing large datasets, aligning closely with the performance of senior expert radiologists [8, 10]. SAH and EDH emerged as particularly challenging subtypes for classification across various machine learning models [10], demonstrating that our fuzzy deep learning model achieves state-of-the-art accuracy in detecting and classifying ICH CT images. Our model enhances the accuracy of detecting and classifying ICH CT images to 100%. The improved accuracy of our model could lead to more accurate diagnoses of ICH CT images, which could improve patient outcomes.

Table 1: Comparison between the proposed fuzzy deep learning model and the state-of-the-art methods in the performance results on brain computed tomography (CT) images dataset

Reference	**Methodology**	**performance**
Yuh et al. [6]	Threshold-based	Sensitivity: 98% Specificity 59%
Li et al. [7, 8]	SVM	Sensitivity: 100% Specificity 92%
Chilamkurthy et al. [9]	CNN (REsNet18) and Random Forest	Sensitivity: 92% Specificity: 70% Average AUC of 0.93
Grewal et al. [10]	CNN(DenseNet)+RNN	Sensitivity: 88% Precision: 81% Accuracy: 81%
jnawali et al. [11]	CNN(ensemble)	Sensitivity: 77% Precision: 80% AUC of 0.87
Arbabshirani et al. [12]	3D CNN	Sensitivity: 71.5% Specificity: 83.5% AUC of 0.846
Lee et al. [13]	CNN(ensemble)	Sensitivity: 78.3% Specificity: 92.9% AUC of 0.959
Ozaltin et al. [14]	OzNet-NCA-ANN	Sensitivity: 100% Specificity: 100% AUC of 1.00
Proposed model	Fuzzy and ResNet50	Sensitivity: 100% Specificity: 100% Accuracy: 100%

5 Conclusion

The proposed ensemble model provides solutions that can assist radiologists in their tasks, reducing their workload and the potential for errors in ICH CT image detection. Early detection allows timely medical intervention, leading to a quicker surgical schedule and better outcomes. This paper proposes a robust fuzzy deep learning model incorporating ResNet50 models with fuzzy logic to differentiate between epidural, subdural, subarachnoid, intraventricular, and intraparenchymal ICH states. The brain CT images dataset was used to create and measure the performance of the proposed model. The dataset was preprocessed by resizing, rescaling, zooming, flipping, contrasting, and rotating images. The proposed model was tested on the brain CT image dataset and compared to competitive methods using the same dataset. The proposed model provided a maximum precision, recall, F1 measure, and accuracy of 100%, 100%, 100%, and 100%, respectively, demonstrating state-of-the-art results. However, the model has some restrictions. The main drawback of the proposed model is that it is not effective when working with large datasets. One of the primary limitations therein is that its overall evaluation focuses on a single type of imaging, which may not reflect all the details of ICH. Furthermore, it also depends upon the quality of the data used as well as the variations available in the data set. Despite the comprehensiveness of the brain CT image dataset, there might be some clinical scenarios not included in the identified and labeled cases, which may affect the generalization of the developed model. Additionally, the implementation of the proposed model has a loss validation of about 0.49, which means that the model has fewer errors. Future work should focus on improving the performance and generality of the developed model, especially the loss validation. Another avenue is to explore the incorporation of other types of images, intermediate to traditional X-Ray.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Author Contributions

Conceptualization, M.A.M., M.K.E. and K.A.; Methodology, S.A.E., M.A.M., A.A.A.; Software, M.A.M. and M.K.E.; Validation, K.A., S.A.E., and A.A.A.; Resources, M.A.M., and M.K.E; Data curation, S.A.E, and K.A.; Formal analysis, M.A.M., and A.A.A.; Investigation, M.A.M.; Project administration, M.A.M.; Supervision, M.K.E.; Visualization, K.A., and S.A.E.; Writing—original draft, M.A.M, and M.K.E.; Writing—review & editing, K.A. and S.A.E. All authors have read and agreed to the published version of the manuscript.

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Author contributions

The authors contributed equally to this work.

Conflict of interest

The authors have no conflicts of interest to report regarding the present study.

Data Availability Statement

Not applicable due to privacy concerns.

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