BRAIN STROKE PREDICTION FROM NEURO IMAGES USING DEEP LEARNING

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ABSTRACT: Brain stroke, a leading cause of disability and mortality worldwide, necessitates early detection and intervention for improved patient outcomes. This study proposes a novel approach for predicting brain stroke using magnetic resonance imaging (MRI) scan images and deep learning algorithm. A dataset comprising MRI scan images of patients with and without strokes is collected and pre-processed to enhance image quality. Features are extracted from the images, capturing radiomic information indicative of stroke pathology and implement deep learning model including convolutional neural networks (CNN), are trained on the extracted features to classify MRI scan images into types of strokes (ischemic and hemorrhagic) and non-stroke categories. Model performance is evaluated using standard metrics, and validated models are integrated into clinical workflows for real-time stroke prediction. The proposed approach offers a promising avenue for early detection and intervention in brain stroke cases, potentially improving patient outcomes and reducing the burden of stroke-related disabilities. The utilization of MRI scan images provides a non-invasive and highly detailed imaging modality for assessing brain health and detecting stroke-related abnormalities. This includes extracting radiomic features from MRI images, which capture subtle variations in tissue characteristics associated with stroke pathology.

KEYWORDS: Brain Stroke, Deep Learning, Convolutional Neural Networks (CNN), MRI Scan Images, Ischemic Stroke, Hemorrhagic Stroke, Radiomics, Medical Imaging, Stroke Prediction, Artificial Intelligence In Healthcare

1. INTRODUCTION

Stroke, a devastating medical condition characterized by the sudden disruption of blood flow to the brain, poses a significant global health challenge. Stroke, often referred to as a brain stroke or cerebrovascular accident, is a critical medical emergency characterized by the sudden interruption of blood flow to the brain. This interruption can occur due to the blockage of a blood vessel (ischemic stroke) or the rupture of a blood vessel (hemorrhagic stroke), leading to damage to brain tissue and potentially life-threatening consequences. Stroke is a leading cause of disability and mortality worldwide, with profound implications for individuals, families, and healthcare systems. With its potential to cause severe neurological impairment, disability, and even death, stroke stands as a leading cause of mortality and long-term disability worldwide, according to the World Health Organization (WHO). Despite advancements in medical science and healthcare, the incidence of stroke remains a pressing concern, highlighting the need for effective strategies for early detection, risk assessment, and intervention. Early identification of stroke warning signs and risk factors is paramount for mitigating its impact and improving patient outcomes. Timely intervention can not only reduce the severity of the condition but also minimize the risk of long-term disability and mortality. Traditional methods of stroke risk assessment often rely on subjective interpretation of medical data and clinical evaluation, which may be limited in accuracy and efficiency. In recent years, the emergence of advanced computational techniques, particularly deep learning algorithms, has revolutionized various domains, including healthcare. Deep learning algorithms, characterized by their ability to automatically learn hierarchical representations from data, offer tremendous potential for enhancing the accuracy and efficiency of stroke prediction and risk assessment. In this diagram specifies the brain stroke information in figure 1.

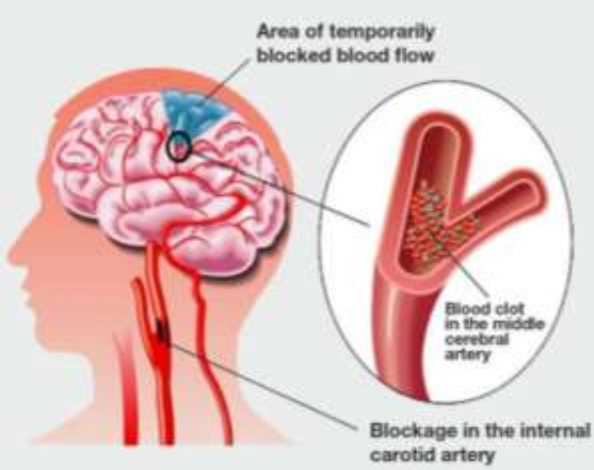

Fig 1: Brain stroke details

In the field of medicine, machine learning has become a powerful technology that has the potential to transform stroke prevention and prediction. Machine learning models use large datasets and sophisticated algorithms to identify hidden risk factors, forecast outcomes, and offer tailored strategies for treatment. Stroke prediction is a vital area of research in the medical field. However, there are several problems and issues that need to be resolved. The accuracy of predictive models is one of the main issues. Machine learning models have shown potential in stroke prediction. Factors such as the data quality, the choice of features, and the choice of algorithm can impact how well models perform. To ensure these model's dependability and efficacy in predicting strokes, it is crucial to assess and validate these factors carefully. Another critical concern is the handling of missing data. Predictive prediction model performance can be severely impacted by incomplete data, producing erroneous or biased outcomes. Appropriate data imputation approaches are needed to handle missing data and increase the precision of prediction models.

2. RELATED WORK

Senjuti Rahman,et.al,…[1] analysed to forecast the possibility of a brain stroke occurring at an early stage using deep learning and machine learning techniques. To gauge the effectiveness of the algorithm, a reliable dataset for stroke prediction was taken from the Kaggle website. Several classification models, including Extreme Gradient Boosting (XGBoost), Ada Boost, Light Gradient Boosting Machine, Random Forest, Decision Tree, Logistic Regression, K Neighbors, SVM - Linear Kernel, Naive Bayes, and deep neural networks (3-layer and 4-layer ANN) were successfully used in this study for classification tasks. The Random Forest classifier has 99% classification accuracy, which was the highest (among the machine learning classifiers). The three layer deep neural network (4-Layer ANN) has produced a higher accuracy of 92.39% than the three-layer ANN method utilizing the selected features as input. The research's findings showed that machine learning techniques outperformed deep neural networks.

Susmita Chennareddy, et.al,…[2] explores the development, functionality, and effectiveness of portable stroke detection technologies used in prehospital environments. It examines various wearable sensors, AI-powered diagnostic tools, and non-invasive imaging techniques that assist emergency responders and healthcare professionals in detecting stroke symptoms outside hospital settings. The review highlights advancements in electro encephalography (EEG), near-infrared spectroscopy (NIRS), transcranial Doppler ultrasound (TCD), and machine learning-based assessment models. Additionally, challenges related to accuracy, portability, cost, regulatory approvals, and integration with emergency medical systems (EMS) are discussed. The findings suggest that while portable stroke detection devices hold great potential in improving stroke care, further research, clinical validation, and technological refinements are necessary to enhance their reliability and widespread adoption.

Smita Patil, et.al,…[3] explores current methods for AIS detection, including clinical assessments, neuroimaging techniques such as computed tomography (CT) and magnetic resonance imaging (MRI), and emerging biomarker-based diagnostics. The diagnosis of AIS relies heavily on advanced imaging modalities that differentiate between ischemic and hemorrhagic stroke, assess perfusion deficits, and guide therapeutic decisions. Treatment strategies for AIS primarily include intravenous thrombolysis (IVT) using recombinant tissue plasminogen activator (rtPA) and mechanical thrombectomy (MT) for large vessel occlusions. Recent advancements in endovascular therapy, neuroprotective agents, and personalized medicine have shown promise in expanding treatment options and improving patient recovery

Tomas Pokorny, et.al,…[4] presents an experimental validation of the Distorted Born Iterative Method (DBIM) combined with the Two-Step Iterative Shrinkage/Thresholding (TwIST) algorithm for accurate stroke identification and classification. A multi-layered anatomically complex head phantom, designed to simulate human brain tissues and cerebrovascular structures, is employed for validation. The proposed approach utilizes microwave imaging techniques to reconstruct stroke-affected regions and differentiate stroke types based on dielectric contrasts. Experimental results demonstrate that the DBIM-TwIST algorithm enhances imaging resolution, improves stroke localization, and achieves high accuracy in distinguishing between ischemic and hemorrhagic strokes. Comparative evaluations with conventional imaging methods, such as computed tomography (CT) and magnetic resonance imaging (MRI), reveal that microwave-based stroke detection offers a low-cost, non-ionizing alternative for real-time monitoring. Furthermore, the algorithm's iterative optimization approach refines image reconstruction, reducing artifacts and improving diagnostic precision.

Olympia karadima, et.al,…[5] presents an experimental validation of the Distorted Born Iterative Method (DBIM) combined with the Two-Step Iterative Shrinkage/Thresholding (TwIST) algorithm for stroke detection and differentiation. The proposed approach is evaluated using a multi-layered anatomically complex head phantom that mimics the human brain's structural and dielectric properties. The aim is to assess the feasibility of microwave imaging-based stroke detection and validate the effectiveness of DBIM-TwIST for accurate stroke classification. Stroke is a leading cause of disability and mortality worldwide, necessitating rapid and accurate diagnosis to improve patient outcomes. The ability to differentiate between ischemic and hemorrhagic strokes is critical, as treatment approaches vary significantly. Conventional imaging modalities such as Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) are widely used for stroke diagnosis but are often limited by high costs, ionizing radiation (in the case of CT), and limited portability. Microwave imaging, an emerging non-invasive technique, has shown promise in real-time stroke detection by exploiting the dielectric property differences between healthy and stroke-affected brain tissues.

Saeed Mohsen et al.[6] described using hyper-parameter optimization to implement ResNext101_32 × 8d and VGG19 models to improve the accuracy of brain tumor detection and classification. These two models have the benefit of being architecturally simple, which can lower computational cost (training time), and they are based on a transfer learning process. The Kaggle repository contained a dataset that was used for testing and training the models. The first of six steps involved uploading the dataset of MRI images, which had been divided into images for training and testing. Image normalization, or pre-processing the MRI scans, was the second step. Determining the total number of training epochs was the third step. The fourth step involved using a fitting function to train the model with the chosen MRI images. The fifth step was to test the prediction capacity of the VGG19 model using the MRI test images. The final step was to evaluate the performance of the model using different metrics on the MRI test images.

In the clinical field, precise imaging is essential to producing accurate diagnoses as demonstrated by Solanki, Shubhangi, et al. [7]. The techniques used to acquire artifacts, such as CT, PET, and magnetic resonance imaging, have an impact on the effectiveness of clinical images. Real images from a magnetic resonance scan may include a great deal of unnecessary and undesired detail. A consequence of Rician noise is magnetic resonance imaging. This survey encompasses all the noteworthy characteristics and the latest research conducted so far, along with its limitations and challenges. Gaining a better understanding of how to conduct new research in an appropriate manner within a reasonable timeframe will be beneficial to the researchers. A generic approach is still needed, despite the significant contributions made by deep learning approaches. When training and testing are conducted on comparable achievement features (intensity range and resolution), these methodologies yield better results; additionally, even the smallest deviation between the training and testing imaginings has a direct influence on the robustness of the methodologies. Future research could be done to identify brain cancers more accurately, using real patient data as opposed to mediocre methods of capturing images (scanners). Classification accuracy may be improved by combining deep features with handcrafted characteristics.

Shah, et al.,...[8] carried out To diagnose brain tumors, VS-BEAM, a unique computer-aided diagnosis algorithm, has been introduced. To determine whether tumors are present in MRI images, the ensemble architecture combines several models. The final abnormality is determined by the algorithm through a voting mechanism, which increases diagnosis accuracy and efficiency. For effective feature extraction, we incorporate Squeeze and Excitation (SE) Attention Blocks into the CNN (Convolutional Neural Network) network. We came to the conclusion that SE attention combined with CNN is more logical than CNN networks alone. Using various classifier algorithms, ensemble learning is employed by the VS-BEAM algorithm. While the second method, also a dense classifier, approaches the multiclass brain tumor classification problem as three binary class classification problems, the first method uses a classical dense network to solve the problem as a multiclass classification. Lastly, a Bayesian classifier that estimates the posterior distribution is used by the third classifier to categorize the tumor. During the evaluation stage, the suggested method for identifying and dividing up brain tumors in MRI pictures meets high performance standards. The end-to-end model showed encouraging outcomes and might be applied in ongoing clinical studies for computer-assisted brain tumor diagnosis.

A teacher-student-based LCDEiT framework for classifying tumors from brain MRIs was presented by Ferdous et al. [9]. The framework consists of an external attention-based image transformer backbone for image classification, and a gated-pooled CNN-based teacher model for knowledge extraction. The need for the large dataset of vision transformers has been offset by the knowledge gained from the teacher model. By adding external attention to the backbone transformer model, which decreases complexity linearly with respect to the number of patches, the quadratic complexity caused by self-attention in the transformer encoder is removed. According to the findings, the transformer-based student model at the core of the suggested framework produces the best classification results, with F1-scores of 0.978 and 0.937 for the Figshare and BraTS-21 datasets, respectively. This illustrates how well image transformers with robust learners can be applied in the field of medical imaging, where quick computation is a critical requirement to start treating a patient who is in critical condition. To address the challenges associated with a higher misclassification rate for lower sample classes, the imbalance dataset handling technique, such as class-wise augmentation, may be used in the future. Even though the suggested LCDEiT model performed better on two different Figshare and BraTS-21 datasets, the model's universality could still be enhanced by expanding the experimental database.

Two research issues, including the security issue with the IoMT environment and the classification of brain tumors, were resolved by Ramprasad et al. [10]. The goal of this work is to offer a comprehensive solution to these issues. The study focuses on securing brain tumor images through the use of TIWT in the MIW implementation. The purpose of this is to safeguard patient privacy and confidentiality when medical data is transmitted over the Internet of medical devices. The goal is to ensure that the source image of the brain tumor is transmitted over a secured environment, thereby preventing attackers from seeing the image. Creating a precise system for classifying brain tumors is another goal of the research. It makes use of transfer learning techniques, namely BWO-GA for feature extraction and a transfer learning-based RU-Net model for segmentation. AlexNet, a transfer learning-based network, is then used to classify the segmented tumor region into benign and malignant tumors. The ultimate goal is to increase the accuracy of brain tumor classification, which will allow for early prediction and possibly save lives. The segmentation operation at the IoMT receiver is carried out using the RU-Net model in order to determine the exact location of the tumor. Furthermore, multilevel features are extracted using BWO-GA, and the best features are selected based on attributes found in nature. Furthermore, an AlexNet that is based on transfer learning is trained with the best features for tumor classification.

3. EXISTING METHODOLOGIES

The most challenging and crucial task in image processing is picture segmentation. Segmentation is the process of breaking down an image into its individual objects or areas and grouping visual elements that have similar traits. A crucial step in digital image processing, segmentation has several uses, including compression, automatic text handwriting interpretation, remote sensing, arthritis diagnosis from joint images, and medical image processing. Any image may be divided into several groups using the clustering algorithms based on similarity criterion like colour or texture. The K-means clustering technique, which separates the picture into K groups depending on how similar the pixels in each cluster are, is implemented in the current system. Brain stroke segmentation involves applying a straightforward algorithm to identify the size and shape of a stroke in an MR picture of the brain. Typically, an MRI or CT scan may be used to diagnose a condition by displaying the structure of the brain. K-means is a frequently used clustering technique that divides the data into K different clusters. In this strategy, clusters are specified in advance, which heavily depends on the early discovery of items that accurately reflect the clusters. Additionally, a fuzzy C-means clustering approach was constructed. However, this algorithm cannot deal with the intricate architecture of brain tissues. Fig 2 shows the existing methodologies for machine learning techniques to predict the brain strokes.

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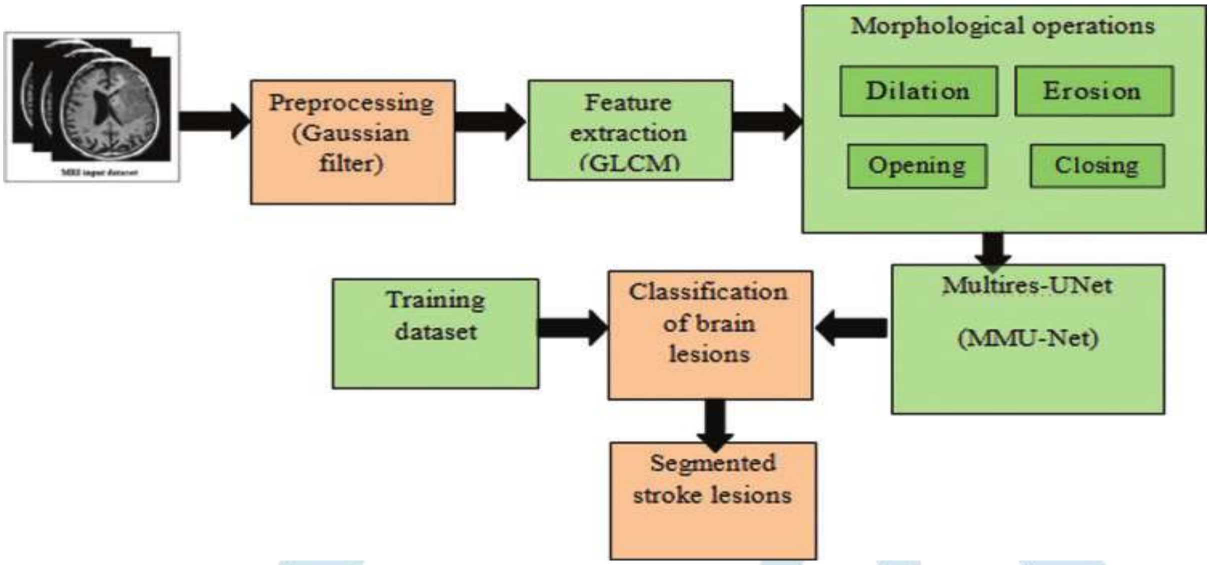

FIG 2: EXISTING METHODOLOGIES

Fig 2 illustrates a process for segmenting brain stroke lesions from MRI images. The process can be broken down into several key stages:

1. MRI Input Dataset: The process begins with an MRI image of the brain, which serves as the input data.

2. Preprocessing (Gaussian filter): A Gaussian filter is applied to the MRI image to reduce noise and smooth the image, enhancing the quality for subsequent analysis.

3. Feature extraction (GLCM): The Gray-Level Co-occurrence Matrix (GLCM) is used to extract textural features from the preprocessed image. These features provide information about the spatial relationships of pixel intensities, which can help distinguish different tissue types.

4. Morphological operations: Techniques like dilation, erosion, opening, and closing are applied to refine the image and remove imperfections.

Dilation: Expands the boundaries of bright regions, which can help fill small holes and connect nearby regions.

Erosion: Shrinks the boundaries of bright regions, which can remove small noise artifacts.

Opening: Typically involves erosion followed by dilation and can remove small objects and smooth contours.

Closing: Usually involves dilation followed by erosion and can fill small holes and connect nearby objects.

5. Multires-UNet (MMU-Net): A deep learning model, specifically a Multires-UNet architecture, is employed for segmentation. This network is trained to identify and delineate the stroke lesions.

6. Training dataset: A labeled dataset of MRI images with marked stroke lesions is used to train the MMU-Net model.

7. Classification of brain lesions: The trained MMU-Net classifies different regions in the MRI image, identifying those corresponding to stroke lesions.

8. Segmented stroke lesions: The final output is a segmented image where the stroke lesions are clearly delineated, providing a visual representation of the affected areas.

This process combines traditional image processing techniques with deep learning to accurately segment stroke lesions, which can aid in diagnosis, treatment planning, and monitoring of stroke patients.

4. PROPOSED METHODOLOGIES

The proposed brain stroke prediction system using MRI scan images employs Convolutional Neural Networks (CNNs) to enhance early stroke detection and improve clinical decision-making. The system follows a structured pipeline, beginning with data acquisition and preprocessing, where MRI scan images are collected from clinical or publicly available datasets. To ensure optimal image quality, preprocessing techniques such as noise reduction, contrast enhancement, and normalization are applied. Additionally, segmentation is performed to highlight the region of interest (ROI), enabling more precise stroke detection.

Following preprocessing, the system utilizes a deep CNN model to extract intricate radiomic features from MRI images, including variations in texture, intensity, and structural abnormalities indicative of stroke pathology. These features play a crucial role in stroke classification, where the model is trained to categorize MRI images into three groups: ischemic stroke (caused by blocked blood flow), hemorrhagic stroke (caused by brain bleeding), and non-stroke cases. The CNN model is trained using labeled datasets, ensuring its ability to accurately detect stroke patterns.

Once trained and validated using standard performance metrics, the stroke prediction system is integrated into clinical workflows, providing radiologists with an automated risk assessment and decision support tool. This AI-powered approach enhances the accuracy and efficiency of stroke diagnosis, facilitating timely medical intervention. Additionally, continuous updates and refinements to the model improve its adaptability and robustness, making it a valuable asset for stroke detection in real-world healthcare applications.

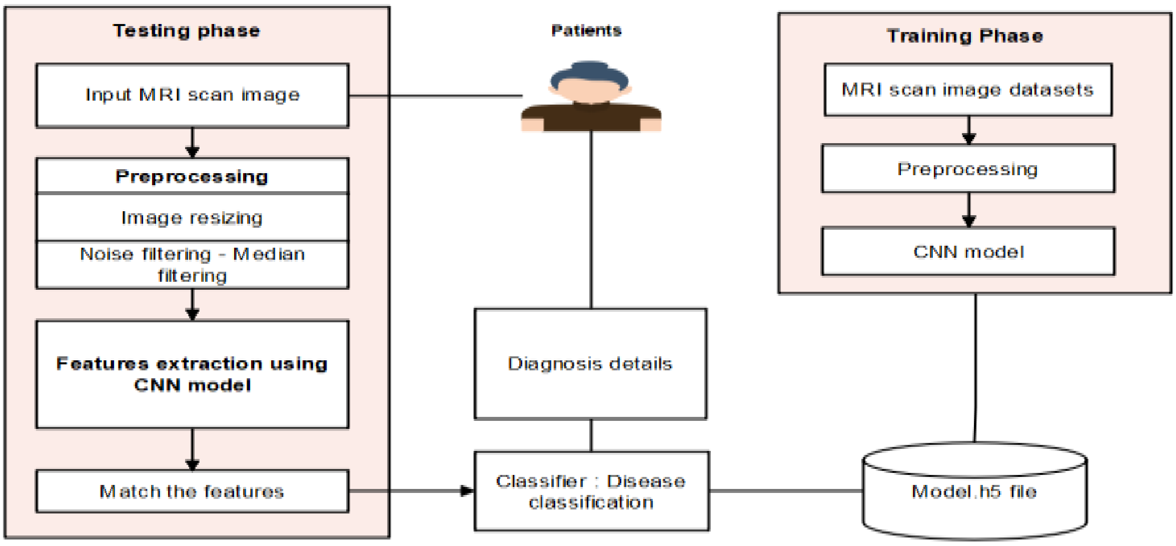

FIG 3: PROPOSED ARCHITECTURE

Training Phase:

MRI scan image datasets: The process begins with a collection of MRI scan images.

Preprocessing: These images undergo preprocessing, which may include resizing and noise filtering.

CNN model: The preprocessed images are then used to train a CNN model.

Model.h5 file: The trained model is saved as a Model.h5 file, which stores the learned parameters.

Testing Phase:

Input MRI scan image: A new MRI scan image from a patient is input into the system.

Preprocessing: Similar to the training phase, the input image is preprocessed, including resizing and noise filtering.

Features extraction using CNN model: The preprocessed image is fed into the trained CNN model to extract relevant features.

Match the features: The extracted features are compared against the features learned by the model.

Classifier: Disease classification: Based on the feature matching, the system classifies the disease.

Diagnosis details: The diagnosis details are then provided as the output.

The diagram shows the flow of data and processes involved in using a CNN model to classify diseases from MRI scans, separating the model training from the testing and diagnosis of new patient data. The proposed modules can be shown as follows

DATASETS ACQUISITION

In this module we can input the CT scan images related to Brain tissues. Images are collected from KAGGLE and it contains two classes named as hemorrhagic 756 files, ischaemic 1087 files. Image can be in the form of JPEG format. Establish collaborations with hospitals, medical centres, and research institutions to gain access to CT scan images of patients with and without strokes. Partnering with healthcare professionals and researchers can facilitate data acquisition and ensure compliance with ethical and regulatory requirements.

PREPROCESSING:

Noise reduction is the process of removing noise from a image. Noise rejection is the ability of an image to isolate an undesired pixel component from the desired image component. In this module perform median filtering algorithm to remove the noises in images. The goal of the filter is to filter out noise that has corrupted image. It is based on a statistical approach. Typical filters are designed for a desired frequency response. Filtering is a nonlinear operation often used in image processing to reduce "salt and pepper" noise. A median filter is more effective than convolution when the goal is to simultaneously reduce noise and preserve edges. In image preprocessing using the median filtering algorithm, the initial step involves importing essential libraries, such as OpenCV and NumPy, to facilitate image manipulation. The target image is then loaded, and optionally, converted to grayscale to simplify subsequent processing steps. The core of the preprocessing lies in applying the median filtering technique, achieved through the cv2.medianBlur() function. This function necessitates specifying a kernel size, determining the neighborhood used for calculating the median values. A key consideration is selecting an odd kernel size, and the choice of this size influences the trade-off between noise reduction and image smoothness. And implement image binarization tasks. Document Image Binarization is performed in the preprocessing stage for document analysis and it aims to segment the foreground text from the document background. A fast and accurate document image binarization technique is important for the ensuing document image processing tasks.

MODEL BUILD

A convolutional neural network is a feed-forward neural network that is generally used to analyze visual images by processing data with grid-like topology. It's also known as a ConvNet. A convolutional neural network is used to detect and classify objects in an image. The CNN architecture is the core of the system. This module involves designing and configuring the CNN model, including defining the number and structure of convolutional layers, pooling layers, fully connected layers, and activation functions. After analysing the structure, each section individually evaluated for the probability of true positives. CNN has two stages; training and testing stage. CNN trains itself by features given as an input to its learning algorithm. During training CNN selects the suitable margins between two classes. Features are labelled according to class associative with particular class. Artificial neural network has a few issues having local minima and number of neurons selection for each problem. In order to resolve this problem CNN occupies no local minima and overhead to neurons selection by initiating the idea of hyper planes. The CNN classifier is a extensively used supervised statistical getting to know classifier this is useful within the case of small schooling samples. The CNN version consists of locating the choicest hyper-plane such that the gap among the hyper-plane, which divorces diverse samples belonging to exclusive lessons, and the closest training sample to it is maximized.

DISEASE PREDICTION:

Once the model is trained and validated, this module enables the system to perform real-time inference. It allows for the automated classification of new MRI scan images as they are input into the system, providing quick and accurate diagnosis

5. EXPERIMENTAL RESULTS

This system forecasts brain strokes using a deep learning algorithm on the front end (Python framework) and a back end (MYSQL). For this study, we can submit the image datasets from KAGGLE interface

TABLE 1 DATASETS DETAILS

DISEASE NAME	IMAGE COUNT
Haemorrhagic	186 files
Ischemic	30 files
Normal	399 files

A hemorrhagic stroke, also known as a brain hemorrhage, occurs when a blood vessel in the brain leaks or ruptures, causing bleeding in or around the brain, which can lead to severe neurological damage

An ischemic stroke, the most common type of stroke, occurs when a blood clot or plaque blocks a blood vessel in the brain, preventing blood flow and causing brain tissue damage.

The training accuracy of the brain stroke prediction system using MRI scan images depends on various factors, including dataset size, preprocessing techniques, CNN architecture, and hyperparameter tuning.

$$Training\ accuacy = \frac{Number\ of\ Correct\ predictions}{Total\ number\ of\ Training\ samples}\ X\ 100$$

Number of Correct Predictions: The count of samples that the model correctly classified during training.

Total Number of Training Samples: The total number of images or data points used in the training phase.

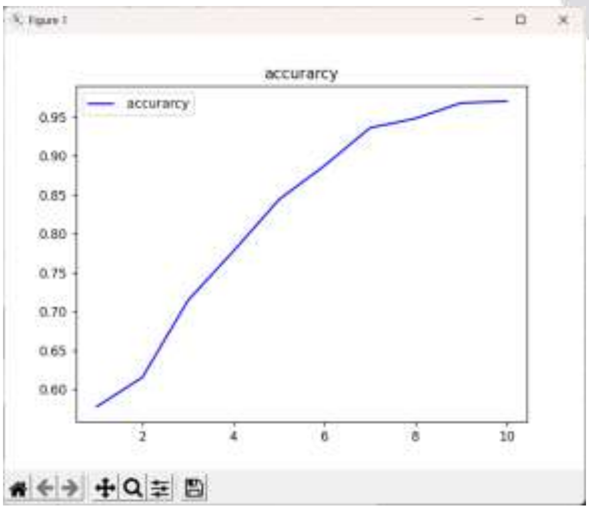

Fig 4: Training accuracy

From the figure, the proposed system achieved 95% accuracy in brain stroke prediction.

6. CONCLUSION

Brain stroke prediction using Convolutional Neural Networks (CNNs) represents a cutting-edge application of artificial intelligence in healthcare, aimed at improving early detection and intervention for stroke patients. By leveraging the power of CNNs, which excel at extracting intricate features from complex visual data, this approach seeks to revolutionize stroke care by enabling automated analysis of MRI scan images for signs of stroke pathology. At its core, the CNN-based approach involves training deep learning models on large datasets of MRI images, annotated with stroke labels, to learn patterns and features indicative of stroke occurrence. These models are trained to classify input images into stroke types (ischemic, hemorrhagic) or non-stroke cases, with the ultimate goal of providing clinicians with early warnings and decision support tools for timely intervention.

REFERENCES

[1] Rahman, Senjuti, Mehedi Hasan, and Ajay Krishno Sarkar. "Prediction of brain stroke using machine learning algorithms and deep neural network techniques." European Journal of Electrical Engineering and Computer Science 7.1 (2023): 23-30.

[2] Chennareddy, Susmita, et al. "Portable stroke detection devices: a systematic scoping review of prehospital applications." BMC Emergency Medicine 22.1 (2022): 111.

[3] Patil, Smita, et al. "Detection, diagnosis and treatment of acute ischemic stroke: current and future perspectives." Frontiers in medical technology 4 (2022): 748949.

[4] Pokorny, Tomas, et al. "On the role of training data for SVM-based microwave brain stroke detection and classification." Sensors 23.4 (2023): 2031.

[5] Karadima, Olympia, et al. "Experimental validation of the DBIM-TwIST algorithm for brain stroke detection and differentiation using a multi-layered anatomically complex head phantom." IEEE Open Journal of Antennas and Propagation 3 (2022): 274-286.

[6] Mohsen, Saeed, et al. "Brain Tumor Classification Using Hybrid Single Image Super-Resolution Technique with ResNext101_32x8d and VGG19 Pre-Trained Models." IEEE Access (2023).

[7] Solanki, Shubhangi, et al. "Brain Tumor Detection and Classification using Intelligence Techniques: An Overview." IEEE Access (2023).

[8] Shah, S. Muhammad Ahmed Hassan, et al. "Classifying and Localizing Abnormalities in Brain MRI using Channel Attention Based Semi-Bayesian Ensemble Voting Mechanism and Convolutional Auto-Encoder." IEEE Access (2023).

[9] Ferdous, Gazi Jannatul, et al. "LCDEiT: A Linear Complexity Data-Efficient Image Transformer for MRI Brain Tumor Classification." IEEE Access 11 (2023): 20337-20350.

[10] Ramprasad, M. V. S., Md Zia Ur Rahman, and Masreshaw D. Bayleyegn. "SBTC-Net: Secured Brain Tumor Segmentation and Classification Using Black Widow with Genetic Optimization in IoMT." IEEE Access (2023).

[11] Rahman, Senjuti, Mehedi Hasan, and Ajay Krishno Sarkar. "Prediction of brain stroke using machine learning algorithms and deep neural network techniques." European Journal of Electrical Engineering and Computer Science 7.1 (2023): 23-30.

[12] Mridha, Krishna, et al. "Automated stroke prediction using machine learning: An explainable and exploratory study with a web application for early intervention." IEEE Access (2023).

[13] Zhu, Enzhao, et al. "Analyzing and predicting the risk of death in stroke patients using machine learning." Frontiers in Neurology 14 (2023): 1096153.

[14] Fast, Lea, et al. "Machine learning-based prediction of clinical outcomes after first-ever ischemic stroke." Frontiers in neurology 14 (2023): 1114360.

[15] Padimi, Vinay, Venkata Sravan Telu, and Devarani Devi Ningombam. "Performance analysis and comparison of various machine learning algorithms for early stroke prediction." ETRI Journal 45.6 (2023): 1007-1021.