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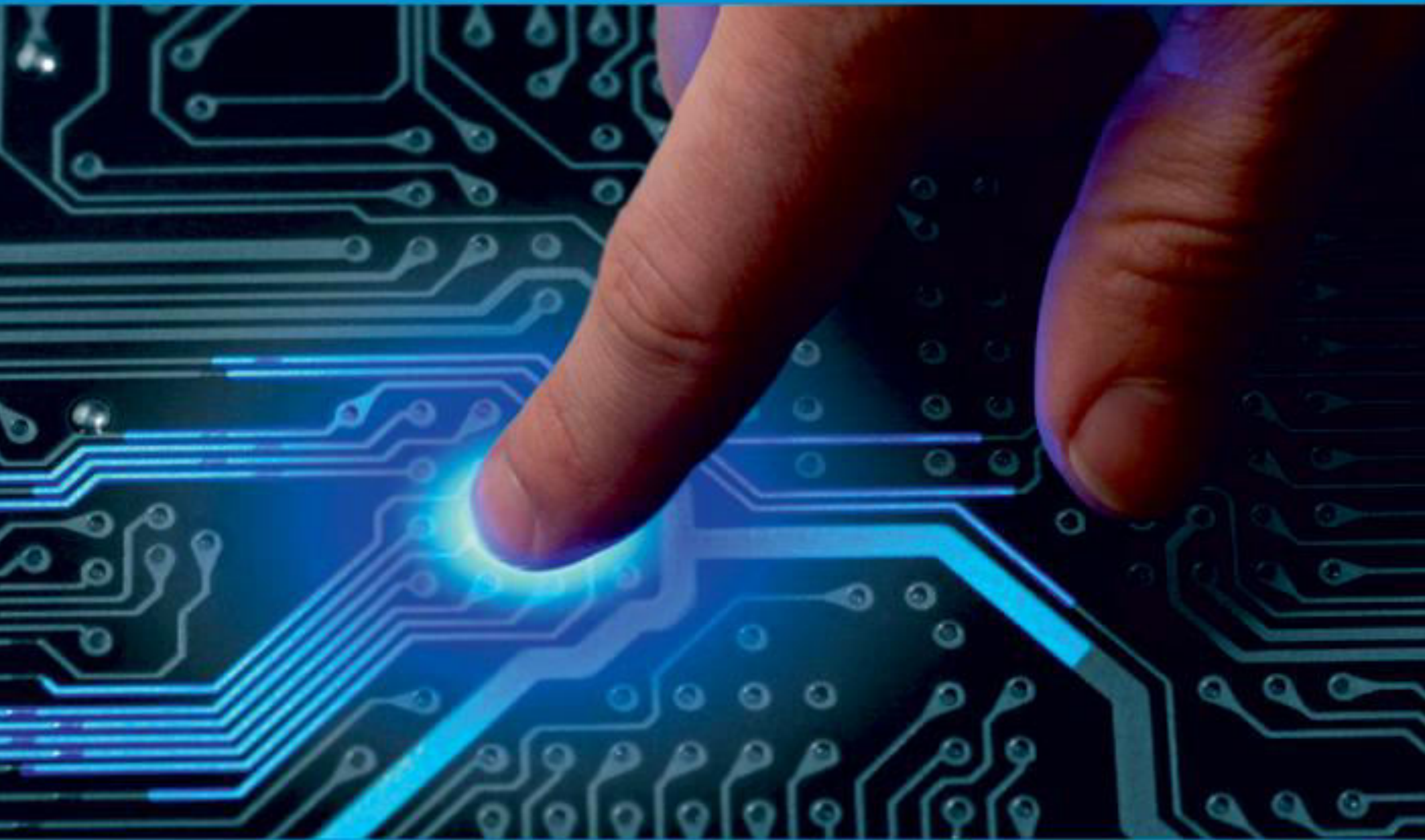

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Approach for Shape Recognition using Multiscale Morphological Processing

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ABSTRACT: Hemorrhage stroke detection with shape priors is a primary role in medical image processing. Since structured segmentation can help with surgical planning and treatment since a perfect characterization of the intended entity's shape can provide a specific localization andstatistical evaluation for subsequent clinical diagnostics likes stroke detection by the characterization of shape of neural tissues. On the additional hand, it is exceedingly challenging due to the massive dimensionality and complicated structures in medical image data. However, there are significant difficulties in medical image segmentation, such as low intensity contrast between blood circulation and complicated shape topology. Furthermore, having a small portion of labelled training samples creates challenges.
Keywords: Brain tumor segmentation, MRI images, Modified Linknet, U-net architecture, Convolutional Neural network, multi-scale prediction, deep learning.

I. INTRODUCTION 1.1OVERVIEW OF THE RESEARCH

A stroke is a neurological disorder in which the brain's blood supply is disrupted, resulting in brain cell death. It is classified two categories named by ischemic and hemorrhagic stroke. Ischemic stroke is associated with low levels of blood supply, whereas, hemorrhagic stroke is caused by immense bleeding in the brain cells. Any of these ailments might cause brain regions to cease functioning correctly. Clinical signs include unable to interact or sense solely on a single area of the body, trouble recalling or hearing, sleepiness, and blurred vision solely on a single side. A stroke's effects and indication ischemic attack (TIA), occurs when symptoms persist only around one to two hours. A hemorrhagic stroke is often followed by a severe headache. A stroke will have long-term consequences. Hypertension is leading source which entails stroke. Tobacco use, overweight, elevated blood pressure, impaired renal function, and ciliary arrhythmias are also health issues resulting from brain stroke.

1.1 TYPES OF STROKES

1.1.1 Ischemic stroke

An ischemic stroke happens when blood flow to a portion of the brain is cut off, causing brain tissue in that range to malfunction. Thrombosis, embolism, systemic hypo perfusion, and cerebral venous sinus thrombosis are among the causes of the anomaly [1]. Cryptogenic strokes (strokes of uncertain origin) account for 30–40 percent of all ischemic strokes. Acute ischemic stroke is classified in a
variety of ways. A stroke can be caused by thrombosis or embolism caused by atherosclerosis of a big artery, an embolism originating in the heart, full blockage of a tiny blood channel, an identified cause, or an unknown reason. Users of stimulants such as cocaineand methamphetamine are at a high risk for ischemic strokes [2].

1.1.2 Hemorrhage stroke

Hemorrhagic strokes are characterized according to their underlying pathology, with hypertensive hemorrhage, burst aneurysms, burst AV fistulas, renovation of earlier ischemic blockade, and medicine-elicited bleed being some of the reasons. They cause tissue harm by compressing tissue as a consequence of the increasing hematoma. Furthermore, the heavinessmay cause effusion of blood to the damaged tissue, ensuing in an infraction, and the effusion of blood by an aspect of hemorrhage have straightforward implication on cerebral tissues. The initial type Intracerebral hemorrhage, which occurs whenever a capillary among the brain rupture, filling strong cells with blood, is caused by intraparenchymal or intraventricular hemorrhage. Subarachnoid hemorrhage (SAH), which originates beyond the brain

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tissue, yet remains inside the skull, and specifically amidst the arachnoids matter and the fragile innermost layer together with 3 plies of meninges that encircles the brain. Abovementioned two primary categories of hemorrhage are indeed two alternative categories of intracranial hemorrhage (ICH), which is blood accretion wherever inside of the skull crypt however, those certain types of ICH, such as epidural hematoma and subdural hematoma are not considered as "hemorrhagic strokes". Changes within blood arteries in the brain, for instance cerebral amyloid angiopathy, cerebral arteriovenous malformation can produce subarachnoid hemorrhage, resulting in hemorrhagic strokes. Hemorrhagic strokes frequently induce particular indications or disclose indications of a previous head injury, in contrast to neurological disability.

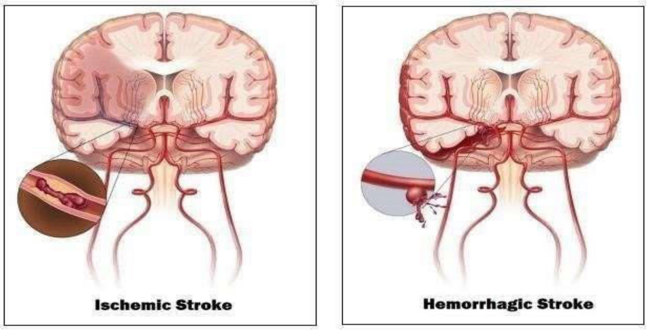

Fig 1: Sketch of ischemic and hemorrhage stroke.

II. LITERATURE SURVEY

A detection over on Stroke plays a substantial role in the suggested methodology. In the upcoming years, the detection process widely uses DL and ML algorithms. This section presents the methods and previous works in blood vessel segmentation and ML-based classification from MRI.

Mrs. Mohammed A. Al-mania et al. [3] proposed A deep automated form of stroke detection named as cerebral microbleeds through deep learning strategy has been developed.The ensemble of regional YOLO based algorithm with the 3D convolution neural network.The proposed research functions to achieve limited false positives to enhance the performance. The conceptual data has been acquired to identify the micro- bleeds obtainedfrom the SWI and the CMBs are analyzed.

Lu Li et al [4] proposed the paper A U-Net based deep learning approach for the effectiveanalysis and segmentation of stroke lesions through computed tomography has been established. Effective hemorrhage segmentation is carried out with the deep learning network. s usually appear soon after it happened. A mini-stroke, also known as a transient The sequence of the flipped image with the image source of CT has been utilized to seek theproposed objective.

Nivedhitha P, Sankar S, Dhanalakshmi R [5] proposed a paper on the detection of brain hemorrhage and their required classification of their types, and presence, absence of stroke have been developed. They can also be used as classifier for decision tree which has been utilize for the categorization of stroke lesion and to conquer over all segmentation. The limitation of the work includes further improvement in the efficient classification of lesion must be carried out for better efficiency.

Hoon Ko et al. [6] presented the paper on an automatic detection and classification of brainhemorrhage with its subsets based on a deep learning (DL) technique. Convolution neural network-long time short memory has been employed for the classification strategy. Windowing has been put into effect individually for brain, subdural and bone window. An exception modeland node for the proposed system has been applied. But the shortcoming includes that the efficiency of windowing must be enhanced for further accuracy of classification performance.

Guanqun Zhang et al [7] presented the paper on the technology of early detection of brain hemorrhage through adaptive transfer. The proposed method has been utilized for central ABP- Arterial blood pressure of waveform in on healthy human in early detection of hemorrhage. By using ABP in lower body of negative pressure it has been subordinated to patients with normal case. To confirm the bleeding, there is an approach of technique been utilized.

Sook Lei Liew et al [8] presented the paper A specific segmentation of stroke lesions through anatomical tracing of

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lesion after stroke (ATLAS) strategy developed. The segmentation is finalized through open-source dataset with T1weighted image. To outperform the performanceof the prior art neuroimaging methodologies the proposed technique has been 28 implemented. The intended system overwhelms the long-term stroke recovery and enables recovery in limited time followed by the therapy. Numerous datasets are involved for testing and trainingof the MRI lesions.

Stefan Pszczolkowski et al [9] presented automatic segmentation of spontaneous intracerebral hemorrhage subsets contingent on MR images promptly. The subsets of ICH such as hematomaand perihematomal oedema are abstracted out by the spontaneous and automated segmentationalgorithm. The specific acute and subacute lesions were segmented out by outlining hematomaand oedema extent directly from MR images. The proposed technic has to be enhanced for further utilization in patientcontact experience.

S Sasikala, Aafreen, Nawresh A [10] A survey on diverse segmentation strategy for the analysis of hemorrhage stroke by operating it either in CT or MRI imaging has been proposed. Miscellaneous segmentation methodology particularly support vector machine, k-nearest neighbor (KNN), Thresholding, Fuzzy-c means (FCM) and so on were reviewed efficiently.

Sudharani, K., Sarma, T.C. and Prasad, K.S. [11] executed a completely unique method for estimating the Identification score, the Classification score, and also for evaluating the stroke area. Clergies, A et a recommend a deep learning methodology for acute and sub-acute stroke lesion segmentation by means of multimodal MR imaging. They pre-process the info to facilitate learning topographies supported the symmetry of brain hemispheres. The risk of sophistication imbalance is tackled using small patches with a balanced training patch sampling strategy.

Zhao, B et al. [12] Presented a a semi-supervised system to automatically segment AIS lesions in diffusion weighted images and apparent diffusion coefficient maps. By employing a sizable quantity of weakly labeled subjects and a little number of fully labeledsubjects, the planned method is in a position to precisely observe and segment the AIS lesions. especially, the process has of three parts: 1) a double-path classification net (DPC- Net) trained during a weakly-supervised way is employed to spot the suspicious regions ofAIS lesions.

G. Thenmozhi, R.A. Jothi, and V. Palanisamy. [13] introduce numerous extraction approaches for diverse databases, including local binary-based methods, dimensionality reduction-based methods, minutiae-based methods, and vein pattern-based methods, as well as equal error rate and recognition rate. Different approaches offer varying levels of security,precision, and robustness. They offered a comparison of several approaches, as well as theirEqual Error Rate.

III. PROPOSED METHODOLOGY

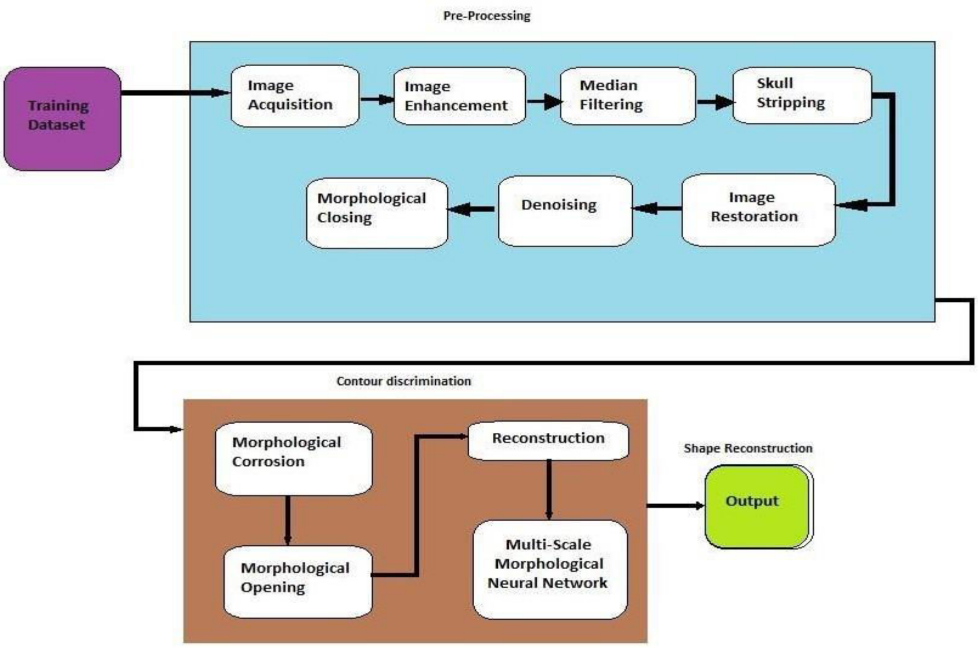

Fig 2: Comprehensive structure of proposed method

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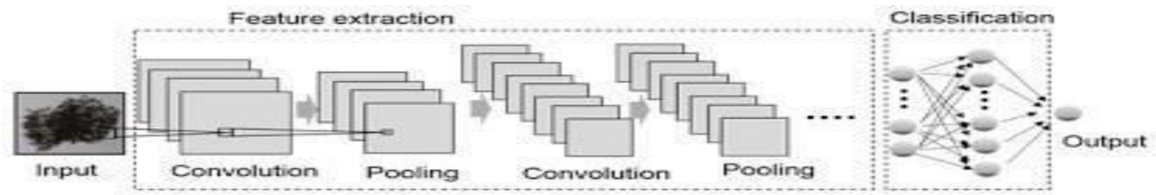

Fig 3: Comprehensive structure of Morphological neural network architecture

The proposed methodology includes various morphological operations for recognizing the proper shapes of the biomedical entities. Here brain is taken for stroke shape recognition withclosing and opening structuring elements. Fig 2 depicts the complete preprocessing steps to achieve the accurate stroke shape.

3.1 MULTISCALE MORPHOLOGICAL NEURAL NETWORK (Multi-MNN)
The convolutional network (CNN) is a type of sharedbe successful in image processing.The position and weight neural network that has been neural shown to orientation of objects are not encoded in deep learning-based CNN and they struggle to categorize images with different positions. CNNs frequently run substantially more slowly, becauseof max pool operations. Moreover, CNN will identify the image as separate patterns madeup of pixel clusters and they do not recognize them as elements present in the image. To overcome the aforementioned challenges, the nonlinear morphological processes are used in place of linear convolutions in deep networks named as Multiscale Morphological Neural Network (MultiMNN).
Based on the input data, the morphological network learns the filters. Technically, theapproach can be divided into three

3.2 Pooling Layer
Pooling layer is used to reduce the dimensionality of feature maps and keep the valuable information at the same time. Different pooling types include max, average, and sum. Inthis thesis, max-pooling is used. So, details of max-pooling are introduced in this section. Max-pooling partitions, an input image into non-overlapping windows and outputs the maximum value in these windows. Benefits of pooling are reducing the size of representation, reducing the number of parameters,and controlling over fitting.

3.3 Fully Connected Layer
A fully associated layer is a neural network that is entirely linked. Every cell in the preceding stage is linked to every neuron in the subsequent stage, according to the phrase "completelyconnected." The input of a fully linked layer is the output of the previous layer. This layer's aim is to utilize these characteristics to categorize the input picture into different classes depending on the training dataset. This layer has the identical characteristics as a multi-layer neural network

3.4 Network Structure
This Paper focuses on an updated approach to the multiscale morphological neural network.In this section, the structure of MMNN is introduced. As previously mentioned, the morphological shared-weight neural network has two stages, which are similar to the convolutional neural network. The difference between them is that the feature extraction stage uses hit-miss transform in MSNNs instead of convolution, which is used by CNNs.

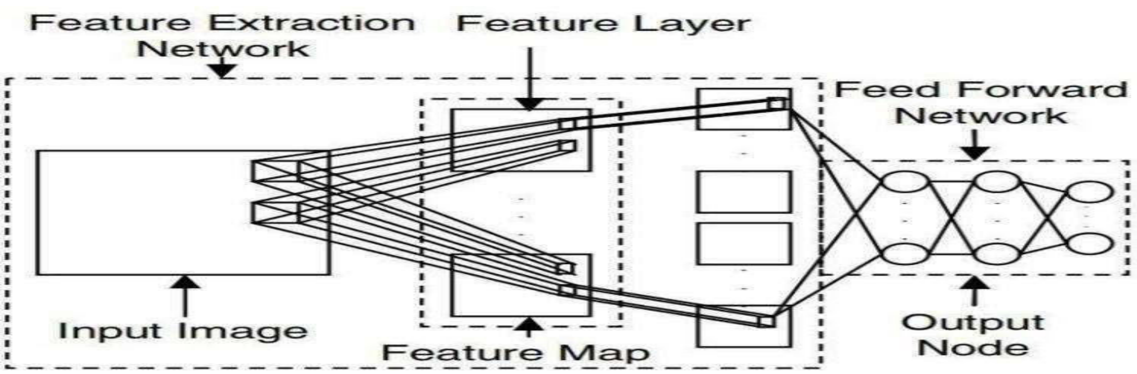

Fig 4: Architecture of morphological shared-weight neural network

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In fig 4 The feature extraction stage extracts feature maps from the input image with hit-miss transform. After max-pooling, the output of first stage is the input of the classification stage. In classification, a fullyconnected neural network recognizes whether the input is a target or not.

IV. RESULT AND DISCUSSIONTHIS SECTION PRESENTS THE QUALITATIVE AND QUANTITATIVE ANALYSIS

4.1 Dataset Description

The brain MRI is extracted using SEIMEN 3T scanner. T1, T2, and FLAIR are used in an MRI scan to obtain a brain image of the patient. The proposed multi-MNN-based weighted MRI sample images and pre-processed analysis are represented in Figures 4 and 5, respectively, with ground truth labels present in each patient's brain image. In the proposedMRI Hemorrhage detection process the brain image of 10 patients were taken using an MRIscanner. T1, T2 and FLAIR sequence were used for extracting the stroke lesions. Fig 5 and6 shows the input Hemorrhage images and pre-processed results of proposed multi-MNN based weighted MRI images respectively.

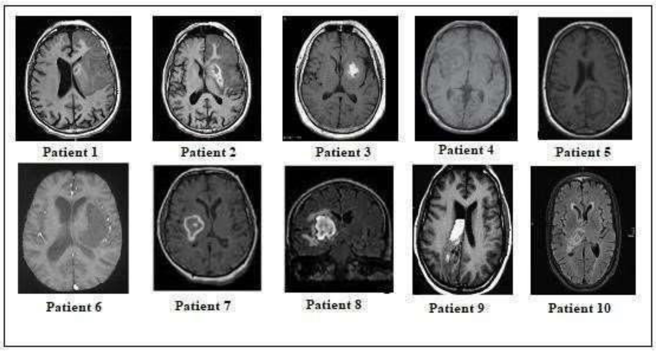

Fig 5: Input Hemorrhage image

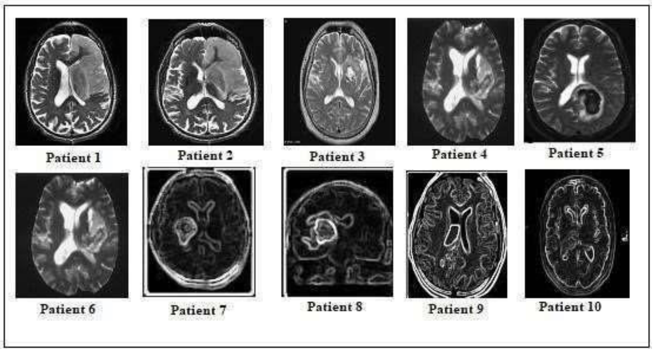

Fig 6: multi-MNN pre-processed MRI image

4.2 PERFORMANCE METRICS

The efficiency of the proposed SSIM method was demonstrated by examining the performance of existing shape recognition techniques such as Convolution neural network (CNN), Residual Convolution neural network, and Morphological convolutional deep neural network (MCDNN) respectively. The comparative analysis was determined using the mean square error(MSE), Structural similarity index (SSIM) and Peak Signal-to-Noise Ratio (PSNR). Fig 7,8 and 9 illustrates the performance metrics of different shape recognition techniques particularly, Residual Convolution neural network, and Morphological convolutional deep neural network (MCDNN) respectively. The iterative measures of PSNR, SSIM and MSE are performed to analyze the performance. When the noise ratio is %1, the proposed morphological attains PSNR of 68.72 and SSIM of 0.999 with the low error rate of 0.03. When the noise ratio is %2,the proposed MNN attains PSNR of 67.98 and SSIM of 0.999 with the low error rate of 0.032.When the noise ratio is %4, the proposed multi-MNN attains PSNR of 69.89 and SSIM of 0.999 with the low error rate of 0.012. When the noise ratio is %6, the proposed MMNN attains PSNR of 68.98 and SSIM of 0.999 with the low error rate 0.017. From this comparative analysis, the proposed MMNN achieves the lowest error rate compared to the existing techniques such as Residual CNN and MCDNN.

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a. Peak Signal-to-noise ratio (PSNR): The PSNR is commonly used as a measurement instrument in image quality evaluation.

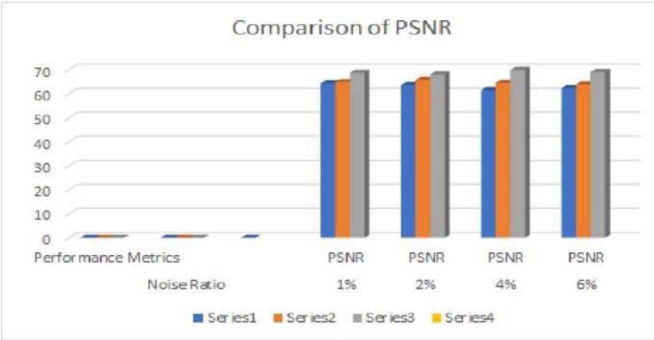

Fig 7: Comparison of PSNR

Fig 7 shows the PSNR comparison of the proposed MMNN with the existing shape recognition techniques such as Residual CNN and MCDNN. The figure clearly shows that the proposed MMNN achieves higher PSNR than other compared methods.

b. Structural similarity index: SSIM is a recent measuring instrument of contrast, luminance, and form, to best accommodate the human visual system's workings. It is a complete comparison of reference and processed images.

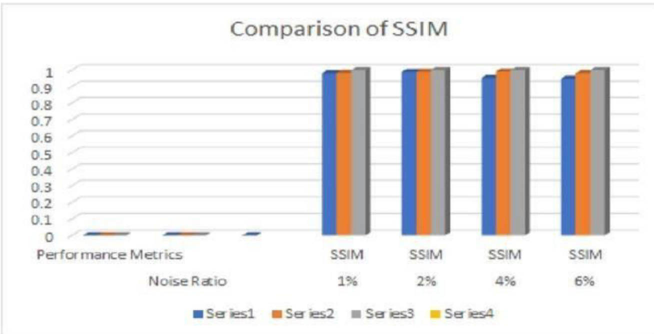

Fig 8: Comparison of SSIM

The result display that the proposed MMNN technique achieves higher SSIM than the existing methods.

c. Mean square errors represents the error ratio between the initial and pre-processed pictures. Used to measure image compression efficiency in which lesser the MSE values imply the presence of lesser error.

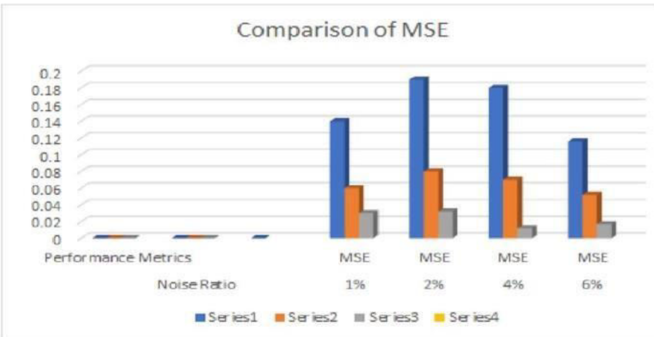

Fig 9 comparison of MSE

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The performance metrics of the proposed MMNN shape recognition technique was evaluated based on theMSE of both the proposed and existing techniques. Fig 9 shows the MSE iteration measures. These iterative measures provide the performance results of this proposed methodology. This research confirms that the proposed MMNN technique outperforms existing shape recognition techniques.

V. CONCLUSION

In conclusion, the utilization of multiscale morphological processing for hemorrhage stroke detection represents a significant advancement in medical imaging and diagnostic techniques.This approach harnesses the power of analyzing images at multiple scales, allowing for enhanced sensitivity and specificity in identifying hemorrhagic strokes. The ability to detect and diagnose hemorrhages promptly is crucial for timely medical intervention, which can significantly improve patient outcomes. Multiscale morphological processing offers a comprehensive and robust methodology for differentiating between normal and abnormal tissue characteristics associated with hemorrhagic strokes. By analyzing various scales of morphological features, the algorithm can capture subtle changes in the image that may indicate the presence of a hemorrhage. This method not only improves the accuracy of detection but also helps minimize false positives and negatives, contributing to a more reliablediagnostic process.

Furthermore, the implementation of this advanced technique holds great promise in improving the efficiency of healthcare systems. Early and accurate detection of hemorrhagic strokes can lead to faster treatment decisions, potentially reducing the overall healthcare burden and improving the quality of life for affected individuals. While further research and validation arenecessary to establish the robustness and generalizability of multistage morphological processing across diverse patient populations and imaging modalities, the current findings suggest that this approach has the potential to revolutionize hemorrhage stroke detection.

REFERENCES

[1] Segmentation of stroke detection by using deep automated for 3D convolution neuralnetwork based on using YOLO algorithm for identify bleedingA. Al-masni et al.

[2] Architecture of U-Net based deep learning approach for the effective analysis and segmentation of stroke lesions through computed tomography has been established by LuLi et al.

[3] Efficient detection based on brain hemorrhage and also classification over other types of stokes by using decision tree classifierhas been utilized to stoke lesion and to conquer over segmentation by Nivedhitha P, Sankar S, Dhanalakshmi R.

[4] Influence the whole mathematical morphological imageprocessingprocess by K.A.M. Said, A.B. Jambek, and NSulaiman.

[5] Sasikala, Aafreen NawreshA survey on diverse segmentation strategy for the analysis of hemorrhage stroke by operating it either in CT or MRI imaging has been incorporated.

[6] Stefan Pszczolkowski et alhave proposed an automatic segmentation of spontaneous intracerebral hemorrhage subsets contingent on MR images promptly. The subsets of ICHsuch as haematoma and perihaematomal oedema.

[7] Sudharani, K., Sarma, T.C. and Prasad, K.Sexecuted a completely unique method for estimating the Identification score, the Classification score, and also for evaluating the stroke area.

[8] A.C. Phan, V.Q. Vo, and T.C. Phancreated a novel mode for automatically detecting, diagnosing, and categorizing brain hemorrhages. This technique relies on analyzing locations of cerebral bleeding using photographs of brain hemorrhage.

[9] The Midline shift was introduced by Liao, C.C., Chen, Y.F., and Xiao, to pre determine the outcomes of intracranial mass patients. Midline shift measuring algorithms that are automated have a lot of potential for helping human specialists in studying brain imaging.

[10] Hssayeni, M.D. et al developed a study methodology to acquire a dataset of eighty-two CT scans of traumatic brain injury patients.

[11] V. Davis and S. Devanesuggested a new method for identifying brain cancer. Hemorrhageis a form of stroke that occurs when an artery in the brain bursts, resulting in bleeding in the nearby tissues.

[12] G. Thenmozhi, R.A. Jothi, and V. Palanisamy introduce numerous extraction approaches for diverse databases, includinglocal binary-based methods, dimensionality

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