Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 32 No. 1 (2025)

Brain Hemorrhage Medical Imaging is Filtered with a PDE Based and Classified using Extracted Features

N. Bhuvaneswari[1]*, R. Sathish Kumar[1], S. Sanjayprabu[2], R. Karthikamani[3]

[1] Department of Mathematics, Sri Ramakrishna Mission Vidyalaya College of Arts and Science, Coimbatore-641 020, Tamilnadu, India.

[2]Department of Mathematics, Rathinam College of Liberal Arts and Science @ Tips Global Institute, Coimbatore-641 107, Tamilnadu, India.

[3]Department of Electrical and Electronics Engineering, Sri Ramakrishna Engineering College, Coimbatore-641 022, Tamilnadu, India. e-mail bhuvaneswari@rmv.ac.in

Article History:

Received: *11-07-2024*

Revised: *26-08-2024*

Accepted: *07-09-2024*

Abstract:

The health and well-being industry stands as one of the most important economic sectors that mostly depend on images. The method described in the investigation's results looks for any possible bleeding. In the most recent study, we suggested a method for using computed tomography (CT) scans to detect hemorrhage in the brain. The recommended method comprises three stages: initial image processing, filtration, and feature extraction. In this study, brain hemorrhage scan images are pre-processed using a ROF filter before hemorrhage incidences are categorized. We extracted features from the head CT picture using the LDP, LPQ, LGP, and NGTDM procedures. Applying the KNN classifier after the features of the images were retrieved produced generally satisfactory results.

Keywords: Brain Hemorrhage, ROF, LDP, LPQ, LGP, NGTDM, KNN.

1. Introduction

Bleeding within the brain tissue is referred to as a brain hemorrhage, cerebral hemorrhage, or intracerebral hemorrhage. There are several reasons why this bleeding may occur, such as trauma, hypertension, anomalies in blood vessels, or illnesses like aneurysms or blood coagulation problems. One kind of stroke is called a brain hemorrhage, which happens when an artery bursts, causing bleeding into or around the brain's tissues. Accident-related injuries can cause inflammation in the brain's structures, which can result in edema—a collection of blood from the tissues around it. Other names for brain hemorrhages include intracranial hemorrhages, cerebral hemorrhages, and intra cerebral hemorrhages [1].

One of the most important parts of a human neurological system that functions properly is the brain. Brain hemorrhages are a potentially fatal condition that can result from physical trauma or medical disorders such as aneurysms or elevated blood pressure [2]. A stroke is an abrupt vascular illness that results in brain tissue destruction from a blood artery blockage or abrupt rupture in the brain. High rates of death, disability, and occurrence are features of stroke. Concurrently, the inquiry reveals that China now has the greatest stroke-related fatality rate [3]. A person's brain is among their most vital organs. A person's abilities and functioning are adversely affected by a serious head injury known as a brain hemorrhage.

Brain CT (Computer Tomography) scans can be used to identify brain hemorrhages. A cross-sectional view is produced by the computer from a series of images captured from various angles by a narrow X-ray beam that circulates the affected body part during a CT scan. The area of the brain experiencing a hemorrhage is difficult to identify and segment [4].After heart conditions and malignancies, brain hemorrhage ranks third in other age groups and is the leading cause of death for those between the ages of 15 and 24.Most of the time, misdiagnosis or delayed diagnosis of hemorrhages is the reason for the death or impairment of certain body organs.

Early identification of the precise location and type of hemorrhage is critical to save the lives of these patients [5]. An example of a specific kind of stroke is a brain hemorrhage, which is brought on by bleeding from a ruptured artery or another cause, like an accident involving an abrupt shift of the brain. Haemostasis, or collections of blood accumulated in the surrounding tissues, are additionally impacted by this kind of stroke. Depending on how much is being bled, the extent of the hemorrhage may require emergency care. Therefore, accurate diagnosis of the organs and brain tissues depends on medical imaging to produce graphical representations of them.

To precisely anticipate the existence of haemorrhage, these medical pictures captured using various modalities, such as CT and MRI, need to undergo additional processing. Various pre-processing processes are performed on the brain CT image in this system. The suggested idea focuses on hemorrhage early identification [6]. The application of technological advances in computers for image enhancement, segmentation, recovery by noise reduction, and other tasks is known as digital image processing technology. Digital image processing technology has advanced and gained new opportunities as a result of the development of computer networks, rising mathematical standards, and the ongoing demand for this technology from a variety of societal industries.

Analysing an image signal using a computer after it has been converted into a digital signal. Image enhancement, noise reduction, segmentation, restoration, encoding, compression, and feature extraction are all included in this procedure. Without advancements in mathematics, computing, and many sectors' growing application needs, technology to process images cannot be produced. Images were processed idealistically using image processing technology, which started to be utilized scientifically in the 1960s. Essential numerous years of advancement, the present state of computerized image processing technology includes several features: increased repeatability when compared to conventional analog image processing, digital image processing eliminates the need for picture storage, copying, or transmission [7].

The following is the information contained order of this paper: Brain hemorrhage imaging modalities are presented in Section 1; image data collection and pre-processing are covered in Section 2; data extraction of LDP, LPQ, LGP, and NGTDM features and characteristics from CT scan images is shown in Section 3; classifier observation is covered in Section 4; results are discussed in Section 5; and the investigation is concluded in Section 6.

I.Data Acquisition

Evaluation of real medical images is difficult for a variety of motives, involving significant basic difficulties. The dataset for brain hemorrhage imaging is available in the Kaggle database. Each scanned set has over a thousand images, which are then separated into multiple formats and rendered available for seeing, depending on whether the scan is for CT, MRI, X-ray, or ultrasound. The radiologists claim that the worries resulting from these aspects and the accuracy of the evaluation do not significantly differ from one another. They demonstrate how a skilled individual may correctly diagnose an issue from a subpar CT image. Two types of photos that show the possibility that there is a brain hemorrhage are included in the files along with 200 head CT scan images.

The patient's head was examined with a CT scanner to determine the degree of the injury to the brain. One hundred injections are normal, and another hundred have bleeding. We can alter the image in our follow-up investigation to ensure that it complies with MATLAB's requirements and guidelines. For example, we could remove deformation and convert RGB head CT scans to grayscale to produce more accurate images. Additionally, this procedure is required because it enhances certain aspects of the image that are critical for subsequently processing and optimizing the visual data. The following procedures are used to prepare CT scan pictures for the conversion from grayscale to RGB.

Figure 1 shows the work flowchart as expected. When the head CT images are being pre-processed or have distortion removed, the proper filter is utilised. The attributes that were developed depend on the evaluation of data from a head CT scan. The acquired characteristics were utilised to adjust the proposed classification algorithms, and outputs were used to assess the classifier's performance.

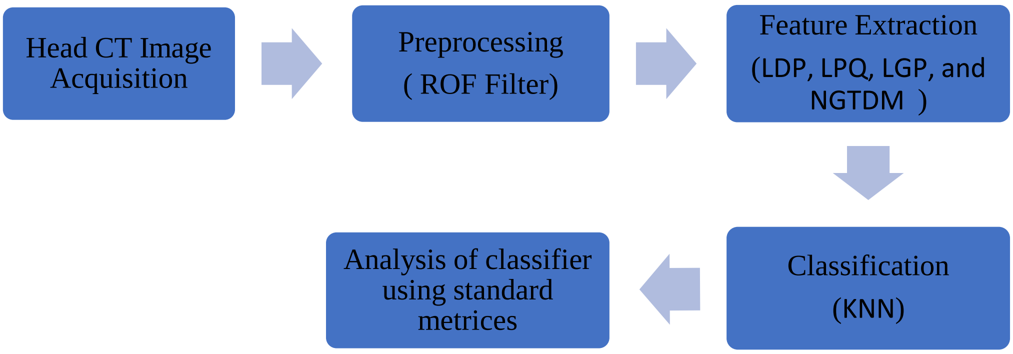


Fig1. Workflow Diagram

Pre-Processing

Pre-processing is the act of removing unnecessary features from the original images so that the focal points stand out over the backdrop. Resizing is an essential step in modifying photos. In addition to visual participation, safety, and shipping, it is necessary for a wide range of other reasons. A scaling operation changes the image's structure. This aligns with the way an individual views the technology in general. The brightness of the CT image is improved by applying grayscale. A 256 by 256-pixel crop is used for the grayscale image processing. The brightness of the image helps to gather accurate tissue-related facts. Accurate tissue transmission of information is made possible by multiple variables. The technique of the recommended therapy is looked at. The appropriate filter is used to reduce noise in head CT images.

II.ROF(RUDIN,OSHER AND FATEMI) Filter

Regularisation serves as the foundation for picture recovery techniques like denoising and deblurring, which are among the most essential tasks in image processing. While challenging, maintaining image edges and features during image regularisation processes is highly desired. It is currently being shown that the ROF model works incredibly well for edge-preserving image restoration. As a result, the model garnered significant interest and was expanded to include vectorial and high-order structures for the restoration of color images [8].The method of total variation regularisation, or denoising, is a technique used most frequently in digital image processing in signal processing.

It can be used to reduce noise. It is predicated on the idea that signals with excessive, potentially fictitious detail have high total variance or a high integral of the signal's absolute gradient. By lowering the overall variance of the signal, provided that it closely resembles the original signal, this method eliminates extraneous information while keeping crucial characteristics like edges. Rudin et al. introduced the idea in 1992 [9]. Earlier techniques for doing this involved the use of least squares, which had the unfavorable characteristic of either softening edges or producing misleading oscillations close to edges—the well-known ringing phenomena, for example.

However, borders and texturing are the most notable aspects of digital photographs. A great deal of research has investigated altered models to lessen this phenomenon, which can remove noise while maintaining edges and small-scale features. The variational models are among the largest and most actively researched fields of mathematical image processing and computer vision research, and they have proven to be highly effective among altered models in a wide range of image restoration challenges. The ROF model is an established variational model [10]. They currently cover other restorative activities including deblurring, blind deconvolution, and in painting in addition to the core issue of picture denoising.

The solutions to these issues are shown via variational models as minimisers' of suitably selected functional analysis. For these kinds of models, the preferred minimization method usually entails solving nonlinear partial differential equations (PDEs), which are obtained as required by the greatest efficiency criteria. In their groundbreaking study on edge-preserving image denoising, Rudin, Osher, and Fatemi (ROF) first presented total variation based image restoration models. One of the first and most well-known applications of edge-preserving denoising based on PDEs is this one. It was specifically created to remove noise and other undesired fine-scale detail from photos while maintaining crisp gaps, or edges.

The ROF model is among the most straightforward variational systems with this particularly desired feature since it is convex. This model is novel in that its regularisation term disfavours oscillations while permitting discontinuity [11].E. Fatemi, S.J. Osher, and L. Rudin suggested an image noise reduction algorithm. With an actual intensity function f and the presumption that $f = u + \eta$, where η is additive noise, exists, they reconstruct the clean picture u. They propose cutting back on the following features:

$$J(u) = \int_{\Omega} |\nabla u| + \lambda \int_{\Omega} (f-u)^2$$

about a particular modifying variable $\lambda > 0$. If u has bounded variation, meaning $u \in BV(\Omega)$, then the expression $\int_{\Omega} |\nabla u|$ denotes the total variation. Hence, the Rudin–Osher–Fatemi algorithm (ROF) is the

Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 32 No. 1 (2025)

name given to the preceding equation. Rudin, Osher, and Fatemi proposed predicting the denoised image u as a solution to the decrease problem.

$$\underset{u \in BV(\Omega)}{argmin} \|u\|_{TV(\Omega)} + \frac{\lambda}{2} \int_{\Omega} (f(x) - u(x))^2 \, dx \, ,$$

When using λ, a positive value is utilized. This one is known as the Rudin-Osher-Fatemi, or ROF, problem. Denoising involves solving an infinite-dimensional reduction issue where the target field consists of all bounded variation (BV) images. A function is in BV (**Ω**) if it is integrable and there is a Radon measure Du.

$$\int_{\Omega} u(x) div \vec{g}(x) \, dx = -\int_{\Omega} \left(\vec{g}, Du(x)\right) \quad for \ all \ \vec{g} \in \ C_c^1(\Omega, R^2)^2$$

Du is a measure that represents the distributional gradient of u. $\mathrm{Du(x)} = \nabla\mathrm{u(x)\,dx}$is the formula for smooth u. For u, the seminorm of total variation (TV) is

$$\|u\|_{TV(\Omega)} \coloneqq \int_{\Omega} |Du| \coloneqq sup \left\{ \int_{\Omega} u \ div \ \vec{g} \, dx : \ \vec{g} \in C_c^1(\Omega, R^2)^2 , \sqrt{g_1^2 + g_2^2} \ \leq 1 \right\}$$

If u is smooth, then TV is equal to the integral of the gradient's magnitude.

$$\|u\|_{TV(\Omega)} = \int_{\Omega} |\nabla u| \, dx$$

The TV component of the lowering promotes variations in the result even while it permits interruptions. The next element advocates for a strategy that looks like the picture that was viewed f. This combination is used by the reduction algorithm to create a denoised image. There is a unique, everlasting minimizer of the ROF problem in L^2if $\mathrm{f} \in \mathrm{L}^2$, and it is independent of changes in f [12].


Fig2. Original Image **Fig3.** Filtered Image

Compared to more straightforward methods like median filtering or linear smoothing, which enhance the appearance of images but take an alternate route by softening along boundaries, this de-noising strategy has advantages. The ROF model filter increases the precision of prediction. The findings of the study are implemented to provide free-of-noise images suitable for feature extraction.

III.FEATURE EXTRACTION

1.Local Directional Pattern (LDP):

The recognized Kirsch kernels serve as the foundation for the LDP. The edge outcomes are taken into consideration, and it depends on eight distinct orientations [13].The local directed pattern approach was proposed by Jabid in 2010. The approach for extracting features was improved and extended. This approach, LDP, has outstanding stability for unpredictability and inherits the features recovered by LBP. Each one of the pixels in the original image is given an eight-bit binary code using LDP. Evaluating the distances between edge reaction values of pixels dispersed in multiple directions allowed for the computation of an 8-bit pattern [14]. Using data on intensity variations surrounding pixels, the LBP operator attempts to encode the fine-grained details of borders, spots, and other local elements in a picture.

Some studies have substituted the magnitude of the gradient for the intensity value at a pixel point subsequently by using the same methodology as the intensity value. Its gradient magnitude and direction data are not encoded; instead, they solely represent the corresponding variations in gradient magnitude in the locations around it. Inspired by this discovery, we put forth an LDP code that encapsulates the texture of the object and determines the edge value responses in multiple directions [15].The Local Directional Pattern feature extraction method is able to recover texture data from images with high accuracy and resilience to variations in lighting and noise. It has been effectively used in several fields, such as industrial assessment, remote sensing, and biological imaging. Like any feature extraction technique, though, its effectiveness can change based on many variables, including the parameters selected and the properties of the images under study.

2.Local Phase Quantization (LPQ):

A method for extracting features from images in computer vision and image processing is called local phase quantization, or LPQ. It is especially helpful for activities like recognizing and classifying textures. Based on an image's phase information, LPQ functions in the space domain. Ojansivu and Heikkila first suggested the Local Phase Quantization operator for texture description. In texture classification, it was demonstrated that the operator is resilient to blur and performs better than the Local Binary Pattern operator. For the initial time, a description for local phase quantization has been assigned to aid in the categorization of blurry textures.

The purpose of LPQ is to preserve an image in its regional unchanging data against artifacts caused by various types of blur. Motivated by this notion, we suggest the LPQ as a successful approach to deal with the concept of variability issue [16]. Local phase quantization (LPQ) is a novel blur-insensitive textural detection method relying on the quantified period of the discrete Fourier transform (DFT) performed in localised image frames. Movement, out-of-focus, and turbulent air blurring are examples of radially symmetrical blur that is indifferent to the algorithms generated by the LPQ operator. To identify textures, the LPQ operator is used.

It is computed individually at each pixel point, and the produced code values are displayed as a histogram. The codes are generated similarly to the LBP approach, as are their histograms. Prior studies have also employed local frequency analysis, commonly known as signal processing techniques, for texture analysis [17].The Fourier phase spectrum's blur invariance feature serves as the foundation for LPQ. Utilising the 2-D short-term Fourier transform (STFT) done across a rectangle neighbourhood at each pixel position in the image, it extracts the local phase details. Only four complex coefficients—corresponding to two-dimensional frequencies—are taken into account in LPQ [18].

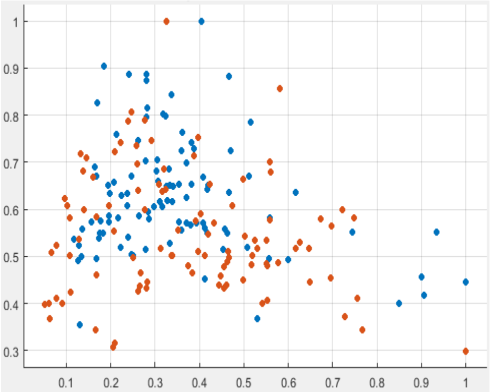
3.Local Gradient Pattern (LGP):

In computer vision and image processing, local gradient pattern (LGP) detection is a method for characterizing the local textural variations in an image. For applications like object identification, texture categorization, and picture recovery, it is especially helpful. Determine the gradient's direction and intensity for all the pixels in the image. The neighbouring pixels for each pixel in an image are considered for calculation in the 3X3 matrix form. The middle square value is going to be used as the reference point. It was calculated to find the size of the distinction between the neighbourhood and central pixels. Subsequently, the average value of every pixel in the 3X3 matrix is calculated. The mean value takes the place of the original value for the central pixel. After that, a comparison was made with the other matrix pixels.

One will be inserted into the newly formed matrix if the related pixel value is larger than the value of the central pixel, and if not, zero will be entered. This led to the formation of a binary pattern. The decimal value corresponding to the binary pattern is calculated, and the central pixel is substituted [19]. Feature vectors are commonly used to depict the gradient patterns once they have been encoded for every pixel. The texture of the picture can be described at various spatial positions using these feature vectors. Ultimately, features are taken out of these representations through the use of methods like statistical measurements, histogram analysis, or using the encoded patterns themselves as features. Because of its adaptability, LGP is a useful technique for obtaining local texture details from images and can be used for a variety of tasks related to computer vision.

4.Neighborhood Gray-Tone Difference Matrix (NGTDM):

Neighbourhood Gray-Tone Difference Matrix is how NGTDM is referred to. It is a technique for feature extraction in an examination of texture that is especially useful for describing tissue textures in medical imaging. By capturing the variations in grey-tone intensities across pixels across a local neighbourhood, NGTDM can provide details about the texture patterns and uniformity of a picture. A particular pixel's divergence from its neighbouring pixel within an acceptable range is measured using the NGTDM. Higher levels of roughness, which gauges brightness shifts among nearby voxels, indicate localised disease homogeneity [20]. Determine the gray-tone intensity differential between each pixel in the image and its surrounding pixels inside the designated neighbourhood. When it comes to tasks like material classification in industrial inspection or tumour classification in medical imaging, NGTDM features are especially helpful in defining the tiny texture patterns found in images.



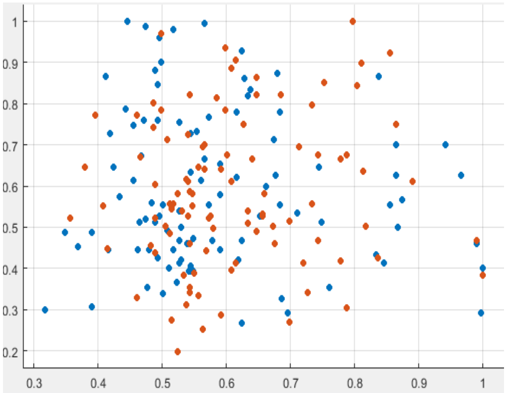
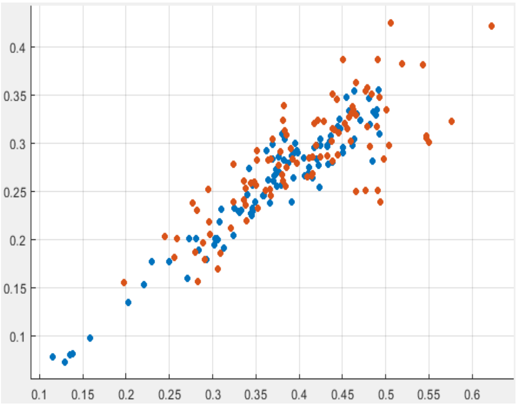


Fig4 : Scatter Plot for LDP**Fig5**: Scatter Plot for LPQ



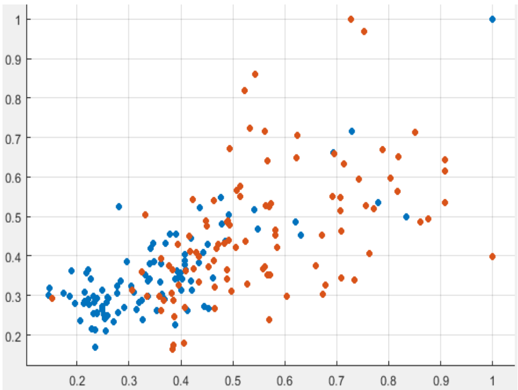


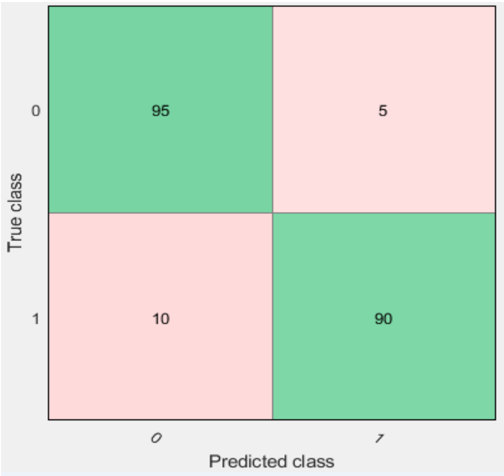
Fig6 : Scatter Plot for LGP**Fig7**: Scatter Plot for NGTDM

IV.CLASSIFICATION

K- Nearest Neighbors (KNN)

Among the most basic and easily understood learning algorithms is k-nearest Neighbour (KNN). KNN is also regarded as an effective algorithm for distribution and execution at the same moment. The supervised learning techniques that this method supports are regression and classification [21]. Since KNN is a non-parametric technique, it doesn't assume anything regarding the statistical characteristics of the data that underlies it. It is often referred to as an instance-based or passive learning algorithm as, in the training stage, it generates forecasts based on the complete training dataset rather than creating a model. The Euclidean distance between the test sample's feature vector and all of the training samples' feature vectors must first be determined to utilise the KNN classifier. Then, using the KNN class labels where k is an integer the unidentified class label is found [22]. For a variety of issues related to classification, KNN is an all-around flexible technique that works well, particularly when the dataset is small or understanding is crucial.

Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 32 No. 1 (2025)



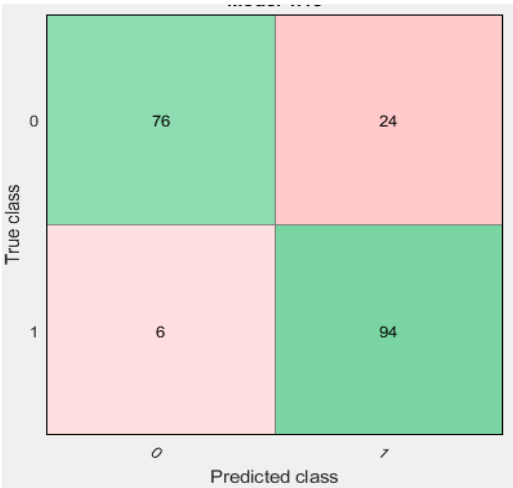
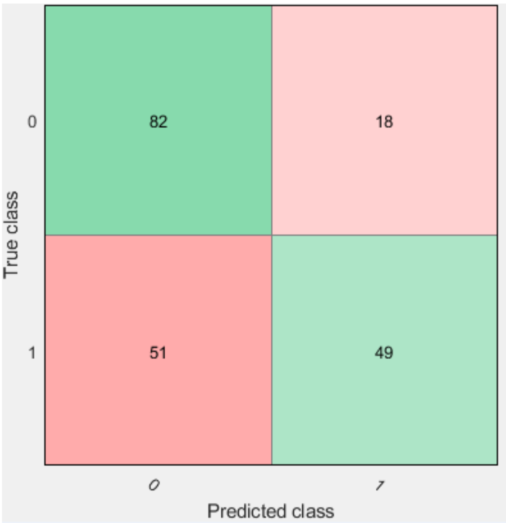


Fig8: Confusion matrix for LDP**Fig9**: Confusion matrix for LPQ



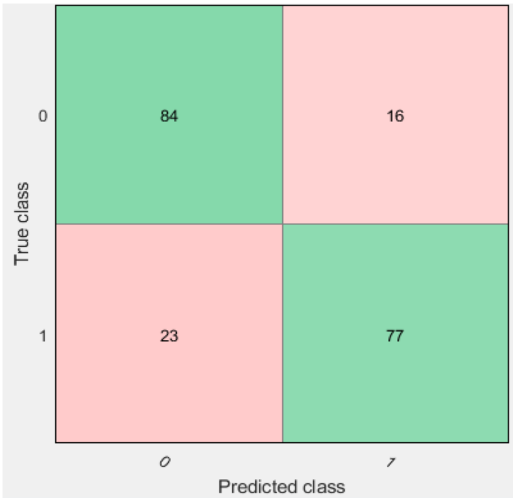


Fig10: Confusion matrix for LGP**Fig11**: Confusion matrix for MGTDM

V.RESULTS AND DISCUSSION

Brain hemorrhage image classification takes into consideration factors such as specificity, sensitivity, accuracy, and false alarm. This method allowed for the utilization of 90% of the collected information for investigation and only 10% for assessment. Sometimes, utilising an assortment of test results for which the true values can be found, a confusion matrix is used to show how well a classification model, often called a "classifier," performs. It enables the evaluation of a procedure's effectiveness. The typical arrangement is as follows:[23].

True Positive (TP): The model forecasted the positive class properly.

True Negative (TN): The algorithm accurately predicted the negative class.

False Positive (FP): A single "Type I error" where the model forecasted the positive class incorrectly.

False Negative (FN): A sort of "Type II error" where the algorithm made an incorrect prediction about the negative class.

The following formulas are used to determine the metrics of specificity, sensitivity, and accuracy:

$$Sensitivity = \frac{TP}{TP + FN} \times 100$$

$$Specificity = \frac{TN}{TN + FP} \times 100$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100$$

$$Precision = \frac{TP}{TP + FP} \times 100$$

$$F1\ Score = 2 \times \frac{Specificity \times Sensitivity}{Specificity + Sensitivity} \times 100$$

$$JaccardMatric = \frac{TP}{TP + FN + FP} \times 100$$

$$BalancedClassifierRate = \frac{Specificity + Sensitivity}{2}$$

$$MCC = \frac{(TP - TN) - (FP - FN)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

Table1: Efficiency of SVM

Parameters(%)	**K- Nearest Neighbors (KNN)Classifier**			
Features	**LDP**	**LPQ**	**LGP**	**NGTDM**
Sensitivity	90.47619	92.68293	61.6541353	78.50467
Specificity	94.73684	79.66102	73.1343284	82.7957
Accuracy	92.5	85	65.5	80.5
Precision	95	76	82	84
F1 Score	9255.751	8568.002	6690.53368	8059.311
Jacard Metric	86.36364	71.69811	54.3046358	68.29268
Balanced Classifier Rate	92.60652	86.17197	67.3942318	80.65019
MCC	1E-06	-3.7E-06	7.4066E-06	1.41E-06

The best result was obtained by comparing the properties using the KNN classifier. The method of extracting LDP features produced a 92.5% accurate outcome with the help of the classifier.

VI.CONCLUSION

MATLAB software was utilized to analyze the significance of identifying characteristics retrieved using LDP, LPQ, LGP, and NGTDM. By utilizing the ROF filter, image noise is decreased. Such filtering effectiveness is assessed using MSE, PSNR, and SNR measurements. When determining the overall averages, we can differentiate between normal and aberrant images utilizing certain feature extraction approaches. The KNN classifier is used to identify the irregularities in the brain hemorrhage. Out of all features, the LDP feature had the highest degree of precision (92.5%) when measured using the classifier. Such an identification of a hemorrhage exposes a large variety of datasets.

References

[1] Ashwini Kadam, Detection and Classification of Brain Hemorrhage Using Ensemble Learning, 2020 IJRAR March 2020, Volume 7, Issue 1.
[2] Dr. Ninad Mehendale, Pragya Gupta, Nishant Rajadhyaksha, Ansh Dagha, Mihir Hundiwala, Aditi Paretkar,Sakshi Chavan, and Tanmay Mishra, A GRAPHICAL APPROACH FOR BRAIN HAEMORRHAGE SEGMENTATION.
[3] Nian Wang, Fei Tong, Yongcheng Tu, Hemu Chen, Yong Zhou, Jun Tang, Extraction of Cerebral Hemorrhage and Calculation of Its Volume on CT Image Using Automatic Segmentation Algorithm, IOP Conf. Series: Journal of Physics: Conf. Series 1187 (2019) 042088.
[4] Krithika M Pai, Region Detection and Segmentation of Brain Hemorrhage using Algorithmic Approach of Image Processing, Journal of Physics: Conference Series, doi:10.1088/1742-6596/2161/1/012070.
[5] Bahare Shahangian, Hossein Pourghassem, Automatic Brain Hemorrhage Segmentation and Classification in CTscan Images, 2013 IEEE.
[6] Dr.E.Thenmozhi, Ms.G.Thejoshree, Ms.U.Nandhini, BRAIN HEMORRHAGE DETECTION USING IMAGE PROCESSING, International Research Journal of Engineering and Technology (IRJET), Volume: 08 Issue: 04 ,Apr 2021.
[7] Congbo Luo, Yunhui Hao and Zihe Tong, Research on Digital Image Processing Technology and Its Application, Advances in Intelligent Systems Research, volume 163.
[8] Xue-Cheng Tai and Chunlin Wu, Augmented Lagrangian Method, Dual Methods and Split Bregman Iteration for ROF Model, Springer-Verlag Berlin Heidelberg 2009.
[9] Dr.PL. Chithra, C. Sermakani, PERFORMANCE ANALYSIS OF IMAGE DENOISING WITH AN ADAPTIVE TOTAL VARIATION AND SHOCK FILTER, International Journal of Applied Engineering Research, ISSN 0973-4562 Vol. 10 No.76 (2015).
[10] Yan Jiang and Shu-Ling Zhang, Image Denoising Based on the Modied ROF Model, 2013.
[11] T. Chan, S. Esedoglu, F. Park, A. Yip, Recent Developments in Total Variation Image Restoration, \Mathematical Models in Computer Vision: The Handbook.
[12] Pascal Getreuer, Rudin–Osher–Fatemi Total Variation Denoising using Split Bregman, Image Processing On Line, 2 (2012).
[13] Y.M. Ayami, A. Shabat, An Acceleration Scheme to The Local Directional Pattern ,2018.
[14] Parmeshwar Khope, Mrs.Vrushali Chakkarwar, Local Directional Pattern for Face Recognition under Varying Illumination Conditions With Deep Learning Methods, International Journal of Research Studies in Science, Engineering and Technology, Volume 9, Issue 1, 2022.
[15] Taskeed Jabid, Md. Hasanul Kabir, Oksam Chae, Gender Classification using Local Directional Pattern (LDP), 2010 IEEE.
[16] M.Belahcene, M.Laid, A.Chouchane, A.Ouamane and S.Bourennane, local descriptors and tensor local preserving projection in face recognition, 2016 IEEE.
[17] Ville Ojansivu and Janne Heikkil, Blur Insensitive Texture Classification Using Local Phase Quantization, Springer-Verlag Berlin Heidelberg 2008.
[18] Sheryl Brahnam, Loris Nanni2,Jian-Yu Shi,Alessandra Lumini, Local phase quantization texture descriptor for protein classification, Bioinformatics and Computational Biology.
[19] Narain Ponraj, Poongodi, Merlin Mercy, Modified Local Gradient Pattern Based Computation Analysis for the Classification of Mammogram, Vol. 14 CIC 2016 Special Issue International Journal of Computer Science and Information Security (IJCSIS).
[20] Khalil, MM, Radiomics Feature Selection in 18F-FDG PET Imaging: Investigation of the Most Robust and Reproducible Candidates,December 2020.
[21] Nuhu Dalhat Mu’azu, Sunday Olusanya Olatunji, K-nearest neighbor based computational intelligence and RSM predictive models for extraction of Cadmium from contaminated soil, Ain Shams Engineering Journal,2023.
[22] Ismail Taha Ahmed, Baraa Tareq Hammad, Norziana Jamil,, Forgery detection algorithm based on texture feature,Indonesian Journal of Electrical Engineering and Computer Science, 2021.
[23] N.Bhuvaneswari; R. Sathish Kumar; S. Sanjayprabu; R. Karthikamani, Detection of Brain Hemorrhage from CT Scan Images using ROF Filter and Classification, 2023 8th International Conference on Communication and Electronics Systems (ICCES), DOI: 10.1109/ICCES57224.2023.10192724.