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DDVM: dual decision voting mechanism for brain tumour identification with LBP²Q-SVM type classifier

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Abstract: Brain tumour classification plays a significant role in medical science as diagnosis of a brain tumour at its early stage of development can improve the recovery of the patient after treatment. In this paper, effective brain tumour presence and type classification methods are proposed. A pre-processing phase of the proposed model is capable to handle the dull medical images by contrast enhancement and noise filtering. In the first phase, to detect the tumour a dual decision voting mechanism (DDVM) for convolutional neural network (CNN) and bidirectional long short-term memory (Bi-LSTM) classification models is proposed. The final tumour identification is done by score maximisation. In the second phase, to identify the type of tumour as high-grade glioma or low-grade glioma, a novel algorithm named LBP²Q featured support vector machine classification model is designed. The results of both phases demonstrated that the proposed scheme outperforms the existing techniques in terms of various performance matrices.

Keywords: biomedical image processing; brain tumour detection; classification model; machine learning; medical image analysis.

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1 Introduction

In medical science, brain tumour is considered amongst the deadliest diseases. In 2019, as per the American Cancer Society, 23, 820 cases of brain tumour were detected in the USA out of which 10, 410 were females and 13, 410 were males. This calculation excludes a non-cancerous tumour called benign. As per their estimation, 17, 660 persons could die from the spinal cord or brain tumour in 2019, out of which 7, 850 were females and 9, 910 were males. The chances of surviving a brain tumour depend upon the tumour’s type and the patient’s age (Das et al., 2019). A stringy mesh of abnormal tissue growth within the human brain is referred to as a brain tumour. This tissue growth is undoubtedly undesirable, but the real concern emerges when it keeps on growing unpredictably. Its unwanted expansion starts to obstruct normal functions of the brain (Shil et al., 2017).

The brain tumour can be classified into two types benign, and malignant. Benign tumours are non-cancerous. On the other hand, malignant tumours are cancerous. Tumours are also classified as either secondary or primary. The primary brain tumour arises from the proliferation of brain cells, nerve cells, membranes, and glands in the human brain. The secondary brain tumour develops in some other body part and from there it travels to the brain (Pries et al., 2018). For efficient therapy, early detection of brain tumours is critical. Images are gathered from a variety of imaging techniques called magnetic resonance imaging (MRI), computed tomography (CT) scan and position emission tomography (PET) scan to detect medical problems (Lather and Singh, 2020). The clinical strategies allow to perform extensive analysis and collect relevant data from the images. The computational approaches assist to analyse the details available in medical images. The brain tumour’s position could be determined by using medical imaging techniques. In comparison to several other imaging modalities such as X-rays, CT scans, MRI delivers more useful data. Brain tumour detection becomes a difficult task because of significant inherent and variable MRI data properties, such as variability in tumour’s shape or sizes, tumour identification, area calculation, classification, segmentation, and to find uncertainty in the segmented region (Garg and Garg, 2021). As a result, brain tumour classification is critical in figuring out what kind of brain tumour a patient is suffering from (Sridhar and Krishna, 2013). To allocate a physical object or occurrence into one of the predetermined sets is referred to as classification. The datasets of medical images utilised for classifying images usually comprise of images of varied modalities, taken under varying situations, with varying degrees of annotation accuracy.

The classification of brain tumours can be performed by utilising supervised schemes such as support vector machine (SVM), several knowledge-based schemes, segmentation approaches, and neural networks. The identification of brain tumours is improved by using a neural network. The neural networks can be classified into various types like k-nearest neighbour (kNN), convolutional neural network (CNN), artificial neural

network (ANN), probabilistic neural network (PNN), deep neural network (DNN) and feed-forward neural network (FNN). The unsupervised schemes such as self-organising map (SOM), fuzzy C-means (FCM) when used in conjunction with techniques for extracting features also help to classify brain tumours (Asodekar et al., 2019).

This paper is organised as follows. In Section 2, existing work related to the classification process is reviewed. In Section 3, the simulation setup and the proposed method are described in detail. In Section 4, results are presented and described in detail along with the comparative analysis of the proposed algorithm with the existing ones on the basis of various performance parameters. Finally, Section 5 concludes the paper by giving the future directions.

2 Related work

In the process of detecting brain tumours, image acquisition is considered as the first step that collects data from various datasets that are obtained from CT scans, MRI, ultrasound, etc. Next comes pre-processing phase, which includes image enhancement, filtering operations, and segmentation. The image is pre-processed to increase the image's quality and decrease the noise. The major aim of pre-processing is to increase the image's smoothness, edge enhancement, and sharpness. The image segmentation step seeks to assess tumour size by estimating region of interest (ROI) and looking at the anatomical composition of various body parts. After pre-processing stage come the post-processing stage, in which feature extraction and detection are performed. Features are extracted from the segmented region by utilising properties of the region such as area, diameter, solidity, and roundness. Feature extraction is considered the most important aspect of any classification system because classifiers depend upon the discriminatory features of the image. In Asodekar et al. (2019), shape-based features were utilised to extract the features from the segmented brain tumour region. In Gumaei et al. (2019), a hybrid feature extraction strategy was suggested to build an accurate classification strategy to detect brain tumours by utilising regularised extreme learning machine (RELM). In Zulkoffli and Shariff (2019), tumour features like contrast, kurtosis, energy, homogeneity, and correlation were extracted by utilising regional and morphological characteristics operation. In Amin et al. (2019), lesion's enhancement, extraction, and selection of important features, and the classification techniques were integrated. To normalise the input image during the lesion enhancement phase, the N4ITK3 technique was used. For fusion and feature extraction, texture-based features such as segmentation-based fractal texture analysis (SFTA) and local binary pattern (LBP), and shape-based features histogram of oriented gradients (HOG) were employed in a serial fusion-based methodology. In Yang et al. (2019), in the local binary mode, the CNN method was compared with numerous conventional algorithms.

In the detection phase, the features extracted from images are given a predefined range of values. If any feature falls inside that range it is categorised as a tumour image or non-tumour image. In Suresha et al. (2020), the K-means and SVM techniques were combined to present a system that decides whether the patient has a tumour or not from the MR image. In Grampurohit et al. (2020), deep learning methods such as VGG-16 architecture and CNN model were used to locate tumour regions in the scanned images of the brain. In Irsheidat and Duwairi (2020), based on artificial CNN, the authors of this paper proposed a model that detects the tumour in MR images and used matrices

operation and mathematical formulas for analysis. In Jia and Chen (2020), based on deep learning techniques a fully automatic heterogeneous segmentation using a support vector machine (FAH-SVM) was presented to segment a brain tumour. In Choudhury et al. (2020), to identify the MRI as ‘TUMOUR NOT DETECTED’ or ‘TUMOUR DETECTED’, a method which utilised DNN and integrates a CNN-based model was suggested. In Sahu et al. (2020), a tumour was detected in the three phases in morphological detection: pre and post processing along with data processing.

Finally comes the classifier training and classification phase, which involves making decisions about tumour class. Several identification features on the tumour facilitate the decision-making process. In Sarkar et al. (2020), an approach was suggested for classifying the brain tumour after including various processing phases followed by feature extraction and segmentation. Finally, the classification of the tumour was carried out. In Nagaraj et al. (2020), CNN-based on deep learning was utilised to classify different types of tumours. In Soumik and Hossain (2020), a three-class deep learning model was used to classify meningioma, pituitary, and glioma tumours. In Wang et al. (2020), artificial chosen features were integrated with the machine learning (ML) features by using a convolutional layer to execute convolution operations to increase recognition rate and efficiency. In Biswas and Islam (2021), a brain tumour classifier capable to work on three different classes of the tumour was designed. In Pathak et al. (2019), CNN was used to classify the tumour, and if the tumour was found it is treated by using morphological operations and watershed segmentation (marker-based). In Ghosal et al. (2019), an automatic approach for classifying brain tumours from MRI data was developed that feeds image slice samples into a CNN-based excitation and squeeze ResNet model. In Ucuzal et al. (2019), a free deep learning-based web-based software was presented, which can be used for tumour detection in brain MRI images and diagnosis by utilising T1-weighted MRI. In Sultan et al. (2019), the CNN, a deep learning model was used for the classification of various brain tumour types.

From the literature studied, it is analysed that in the domain of brain tumour detection, the current approaches are working generally in two phases: one is on segmenting the region of interest and secondly classification of the tumour. This classification phase is further subdivided into two areas; one is to determine the presence of the tumour and the second is to recognise the type of tumour. Several strategies were recommended in recent years. Currently, deep learning algorithms are the main focused areas for tumour classification. CNN is gaining much interest by researchers in multiple domains due to its advanced properties such as learning from direct input without any specific feature extraction. But in order to improve the classification rate relying on CNN is not enough; a number of other approaches are also available. Those can be focused on for the future classification model. Even the CNN has its own advantages, as it proved itself to be an effective classification model, therefore working with a collaborative approach can push the current models toward an effective and accurate classification model. Other than this, there are very few models available that are working in both classification phases as classifying the existence of tumour as well as on classifying the type of the tumour.

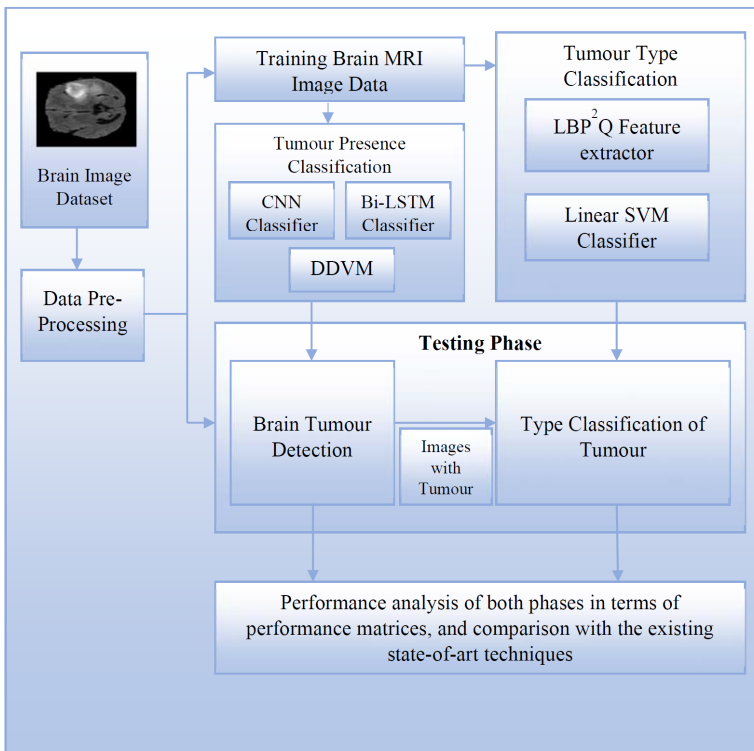
Inspired by this an approach is designed and given in this study that is focused on providing an effective solution to detect the tumour in medical images along with classifying its type. This paper’s important focus is to offer a solution for biomedical image processing based on brain tumour detection and classification. The proposed

model will be capable to effectively determine the presence of the tumour along with its type. The model’s tumour detection phase is based on the combined model of deep learning algorithms and types are classified by using the machine learning approach. Therefore, the proposed scheme is a combined package of current artificial intelligence (AI)-based learning approaches (both machine and deep learning). The simulations are performed in MATLAB software and results demonstrated that the given scheme is superior in terms of categorisation rate, and other performance factors when compared to various state-of-art algorithms.

3 Simulation setup and methods

The research attempts to detect brain tumours automatically, with the added capability of distinguishing their types using MRI images of the brain. The proposed system is working on a dual decision voting mechanism (DDVM) by using convolutional neural network and bidirectional long short-term memory (CNN-BiLSTM) architecture in order to detect the tumour from MRI images. For recognising the tumour type, the local binary pattern and phase quantisation (LBP²Q) featured SVM model is designed in this study. Figure 1 depicts the suggested model’s and workflow’s architecture. The figure shows the pictorial representation of the proposed system and its phases. The proposed system is also evaluated by considering the impact of speckle and Gaussian noise on the original image.

Figure 1 The architecture of the proposed model (see online version for colours)



3.1 Dataset used

The proposed model is using brain MRI images collected from the BraTS MICCAI brain tumour dataset (Menze et al., 2015; Kistler et al., 2013). As the proposed model needs the image to have multiple labels to train the classifiers for doing all the diagnosis steps, the BraTS dataset is having images with labels of normal and tumour brain images. Along with this, it also has two types of tumours such as high grade gliomas (HGG) and low grade gliomas (LGG).

3.2 Data pre-processing

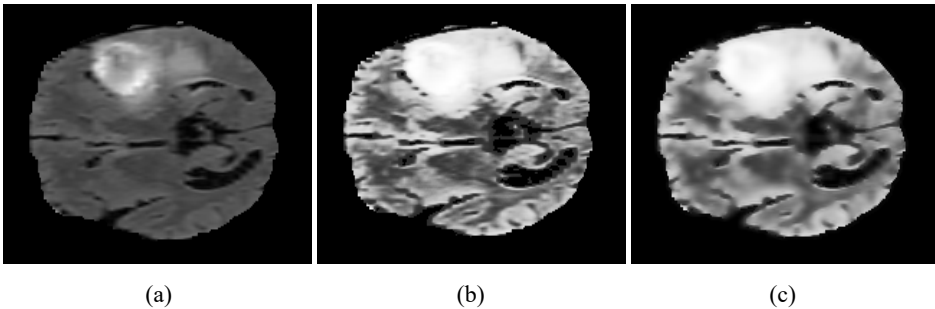
This phase involves the processing of the raw brain MRI images to obtain the format that is required for further processing. In this process, the original MRI images are initially enhanced by using an advanced image enhancement approach named minimum mean brightness error bi-histogram equalisation (MMBEBHE). This technique not only improves the visual properties of the image content but also preserves the brightness which makes it a superior choice to enhance images in comparison to histogram equalisation (HE), brightness preserving bi-histogram equalisation (BBHE), and other variants of histogram equalisation approaches (Butola et al., 2015). The reason behind it is that the histogram of the input image is separated by using a threshold value that gives minimum absolute mean brightness error (AMBE). In this approach, AMBE is calculated at different threshold levels using equation (1).

$$AMBE = |E(x) - E(y)| \quad (1)$$

where $E(x)$ is the mean of an input image and $E(y)$ is the mean of an output image. The threshold level which yields minimum AMBE is considered to separate the histogram and finally, equalisation is performed to preserve the brightness.

Other than enhancing the image content, image filtration is also applied to the enhanced images. The main reason to apply filtration is to reduce the impact of noise which is caused due to medical equipment or the communication channel. For this, a combination of Wiener and bilateral filter is used in this study that combines the properties of reducing the mean square error and preserving the edges of the denoised image. The outcomes of individual phases of data pre-processing are shown in Figure 2.

Figure 2 The experimental output of the data pre-processing phase, (a) original image (b) enhanced image (c) pre-processed image



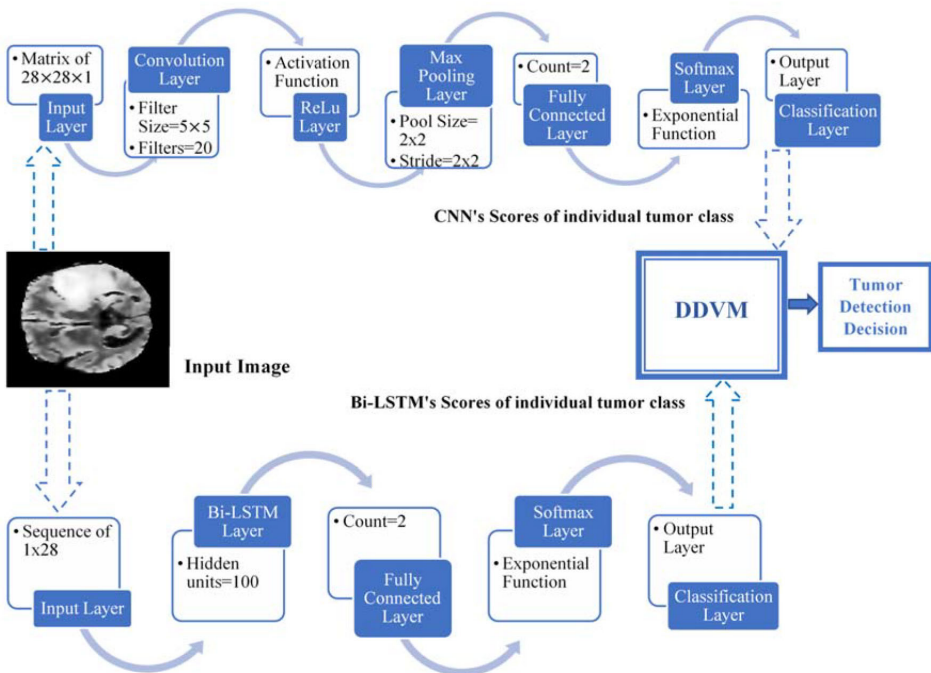
3.3 Brain tumour classification module

This module is a blend of two phases; one is classifying the brain tumour existence and the other is predicting the type of the tumour.

3.3.1 Phase 1

In this phase, a novel scheme is proposed in this paper that is working on a DDVM. The DDVM is using dual classifiers one of them is CNN and another is the Bi-LSTM architecture of recurrent neural network (RNN). The main reason behind using both the CNN and Bi-LSTM networks in parallel is that the conventional CNN network is effective enough to extract the feature from the input images. CNN is proved to be effective in multiple computer vision applications where direct images are passed to CNN for extracting features and further using it for classification. Another property of CNN is that it follows a hierarchical model where it builds the network similar to funnel and finally gives outcomes at the output layer where every neuron is coupled to every other neuron. These properties of CNN strengthen the proposed scheme decision to use CNN for classification in parallel to the Bi-LSTM network. On the other end, the Bi-LSTM network stores the historical information with an additional feature of evaluating the two-way relationships between data. In our application different patterns of brain tumour exists in the dataset. Therefore, it is required to understand the relation or pattern formed between the inputs given to the network. Concluding these factors, our input image set is fit for the Bi-LSTM network.

Figure 3 The network architecture of the proposed DDVM tumour detection scheme (see online version for colours)



3.3.1.1 Network architecture

The architecture of the proposed DDVM model along with details of layers used in the proposed scheme is given in Figure 3. The input image after pre-processing is passed to both the network at the input layers. The CNN has seven layers: an input layer, followed by a convolution, a ReLu, and a pooling layer. Finally, a fully connected layer along with SoftMax and the classification layer is applied to achieve the classification results. Whereas in Bi-LSTM-based network, the input layer is connected to the Bi-LSTM layer to form the Bi-LSTM algorithm's network, after that the three layers for output are similar as it was there in the CNN phase. Once the training of the network is done, the scores from the individual network for both the classes are passed to DDVM where on maximisation score-based final tumour detection decision is given.

3.3.1.2 Training and decision of tumour detection model

For the training of the network, the processed image dataset is separated into training and testing sets. The network is trained using Adam optimiser, with the other training parameters mentioned in Table 1. The training of the network gets stopped after the number of epochs gets completed and reducing the training loss factor. Once both the network gets trained the output layer of CNN and Bi-LSTM network provides scores to individual classes (tumour or non-tumour), then the voting mechanism is used to give the final decision. The scores of both the classes given by CNN and Bi-LSTM are combined by summation of scores. Finally, the class with a higher score is labelled as the output decision.

3.3.2 Phase 2

In this phase, for classification of the type of the tumour, local binary pattern and phase quantisation (LBP²Q) featured SVM classifier is designed. The input dataset is having two classes HGG and LGG which represent the types of tumour. Once, phase 1 classify that whether the image is having a tumour in it or not, two conditions are working in order to pass the image to phase 2 for classification of the type of the tumour. These conditions are given below:

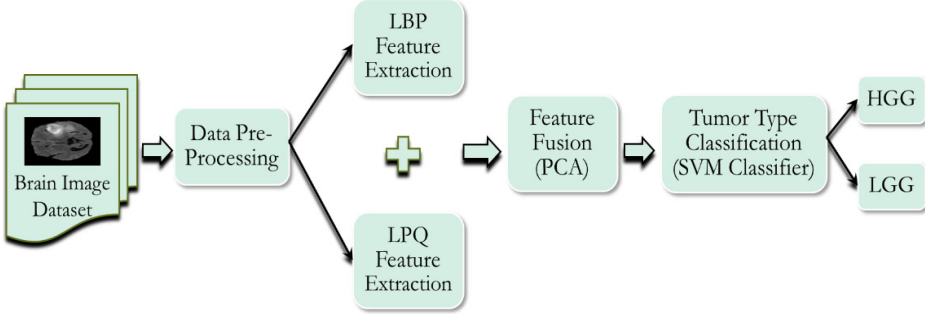
- 1 If the image is having a tumour in it:
Pass the image to LBP²Q featured SVM classifier.
- 2 If the image is not having a tumour in it:
Stop processing as no tumour detected.

3.3.2.1 LBP²Q featured SVM model

Classification of the type of tumour is crucial as after identifying the type the tumour can be timely diagnosed. The texture features serve as a very powerful input in applications where the task is to classify objects as per their patterns. Here in our work, the problem is to detect the type of tumour which can be effectively identified by recognising the texture of the tumour. Therefore, in our proposed scheme, the binary patterns and phase quantisation of input images are done and individual patterns are fused to train the SVM

a machine learning algorithm. The architecture of the proposed LBP²Q featured SVM model is given in Figure 4.

Figure 4 The architecture of the proposed LBP²Q featured SVM model for tumour type classification (see online version for colours)



The reason for choosing these texture descriptors for our application is that the binary pattern is considered to be the most powerful texture descriptor in the area of computer vision (Baskar et al., 2020), and is very simple to implement. In the LBP algorithm, the labels r and p are defined as radius and total points respectively. The binary patterns generated for neighbourhood pixel by the neighbour pixels are working on the concept of thresholding of the centre pixel. The label value of an individual pixel in an image is given by equation (2):

$$LBP(p, r) = \sum_{p=0}^{p-1} k(h_p - h_b) 2^p \quad (2)$$

where $k(x)$ is a constant having value 1 for $x \geq 0$ and 0 for $x < 0$, and h_p , h_b are the grey value of neighbourhood pixels and the centre pixel respectively.

The LBP feature extractor provides the structural features in the spatial domain, but while working with texture content it is recommended to get the frequency domain's patterns too. As our data is brain MRI images, there are numerous effects of machinery while capturing MRI, therefore it is required to have a feature set that should be blur invariant. Even though in the pre-processing phase image enhancement and filtration is applied but blur may exist in the images. To cover the frequency domain's feature and with a property of blur invariancy local phase quantisation (LPQ) technique is used in the proposed work. In this technique, local phase information is extracted by computing 2D short-term Fourier transformation (STFT) over a rectangular neighbourhood $neigh(x_1, y_1)$ (Nanni et al., 2020; Zhang et al., 2016). The 2D STFT on pixel (x_1, y_1) is given as in equation (3).

$$P_{(x1,y1)}(u, v) = \sum_{(x1',y1') \in \text{Neigh}(x1,y1)} p(x1-x1', y1-y1')e^{-(j2\pi u x1' + j2\pi v y1')} \quad (3)$$

While extracting the features the local Fourier coefficients are computed at every pixel concerning four frequency points such as $Q1 = [0, \alpha]^T$, $Q2 = [a, 0]^T$, $Q3 = [a, \alpha]^T$, and $Q4 [a, -\alpha]^T$, where a satisfies $H(\alpha, \alpha) \geq 0$, and $H(\alpha, \alpha)$ is the STFT of the point spread function $h(\alpha, \alpha)$. For each pixel, the resultant vector is given by equation (4).

$$P_{(x1,y1)} = [P(Q1, (x1, y1)), P(Q2, (x1, y1)), P(Q3, (x1, y1)), P(Q4, (x1, y1))] \quad (4)$$

After that binary scalar quantiser is used to quantise the complex parts signs for the individual coefficient. The output 8-bit binary coefficients are converted to integer values to form the pattern.

Finally, both the patterns for spatial and frequency domain are clubbed and fused by using the principal component analysis (PCA) fusion technique to reduce the count of features and get more informatics set. This will also assist the proposed algorithm to be less complex. The final fused feature set is given to SVM classifier for the training. The kernel function used for the proposed SVM classifier is a linear one. After training the network with a dataset of HGG and LGG labelled MRI image set, classification is performed as per the flow given in architecture in Figure 1. The final results are analysed and evaluated for both the phases, i.e., tumour detection and type classification. Different scenarios are considered while developing proposed LBP²Q featured SVM such as initially normal SVM classifier is designed, then as a modification SVM is clubbed with LBP and LPQ individually to understand the improvement. Then the final approach with a fused feature of binary pattern and phase quantisation is designed in order to achieve high classification accuracy.

4 Results and discussion

This section presents the results of the proposed classification system which are obtained by applying it on brain MR images. To simulate the proposed system, MATLAB software is utilised, which needs a minimum of 4 GB RAM, Intel i3 processor, and the latest version of Windows OS. In MATLAB software, the potential of the model is analysed and compared to that of the conventional models. The developed framework is functioning into two phases, the first of which employs a DDVM approach, that detects whether the brain tumour is present or not. In the second phase, LBP²Q featured SVM is used that categorises the detected brain tumour into HGG or LGG. The proposed scheme is evaluated in three different cases: first with no input noise, then considering speckle noise with noise variance of 0.01, and finally, Gaussian noise with noise variance of 0.01 added to the original image to evaluate the performance of the proposed pre-processing phase on classification. The configuration and specification information of the proposed framework is given in Tables 1 and 2.

Table 1 Configuration of DDVM for tumour detection phase

<i>S. no.</i>	<i>Parameters</i>	<i>Network</i>	<i>Value</i>
1	Max epochs	CNN, Bi-LSTM	100
2	Gradient threshold	CNN, Bi-LSTM	1
3	Number of layers	CNN, Bi-LSTM	7, 5
4	Min batch size	CNN, Bi-LSTM	27
5	Input layers size	CNN, Bi-LSTM	28 × 28, 28
6	Convolution filter window size	CNN	5 × 5
7	No. of filters	CNN	20
8	No. of stride	CNN	2 × 2
9	No. of pool size	CNN	2 × 2
10	No. of hidden units	Bi-LSTM	200
11	Output size	CNN, Bi-LSTM	2

Table 2 Configuration and specification information of proposed scheme

<i>S. no.</i>	<i>Parameters</i>	<i>Network</i>
1	Wiener filter window size	5
2	Bilateral filter sigma 1 and 2	3, 0.3
3	Bilateral filter window size	5
4	Training testing ratio	70/30
5	SVM kernel function	Linear
6	SVM kernel scale	1

4.1 Performance measures

The effectiveness of the proposed classification system is evaluated by using the performance measures such as accuracy, sensitivity, specificity, Jaccard, Dice and positive predictive value (PPV) for the three different cases:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (5)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (6)$$

$$Specificity = \frac{TN}{TN + FP} \quad (7)$$

$$Jaccard = \frac{TP}{TP + FP + FN} \quad (8)$$

$$Dice = \frac{2TP}{2TP + FP + FN} \quad (9)$$

$$PPV = \frac{TP}{TP + FP} \quad (10)$$

where TP is the true positive, i.e., tumour pixel is detected as a tumour pixel. TN is the true negative, i.e., a non-tumour pixel is detected as a non-tumour pixel. FP is the false positive, i.e., a non-tumour pixel is detected as a tumour pixel. FN is the false negative, i.e., tumour pixel is detected as a non-tumour pixel.

4.2 Performance evaluation

4.2.1 Phase 1: detecting tumour with DDVM approach

The results obtained by the proposed DDVM approach for tumour detection for the different performance parameters such as accuracy, sensitivity, specificity, Jaccard, Dice, and PPV are shown in Figure 5(a). The proposed DDVM approach resulted in an accuracy of 99.367%, sensitivity 100%, specificity 100%, Jaccard 98.833%, Dice 99.413%, and PPV 98.833%. To further prove the robustness of the proposed algorithm to noise effect, we added speckle and Gaussian noise with variance 0.01 to the original MR image. The results obtained by the proposed DDVM approach for the different performance parameters with regard to different cases of noise, i.e., speckle noise with variance 0.01, and Gaussian noise with variance 0.01 are shown in Figures 5(b) and 5(c) respectively. For the speckle noise case, the proposed DDVM approach resulted in an accuracy of 99.156%, sensitivity 100%, specificity 100%, Jaccard 98.450%, Dice 99.219%, and PPV 98.450%. For the Gaussian noise case, the proposed DDVM approach resulted in an accuracy of 98.945%, sensitivity 99.213%, specificity 99.213%, Jaccard 98.055%, Dice 99.018%, and PPV 98.824%. From the results, it is clear that the classification results remain firm to the noise type proving its robustness to the noise.

Figure 5 Performance analysis of the proposed DDVM model with (a) no input noise, (b) speckle noise of variance 0.01 and (c) Gaussian noise of variance 0.01 (see online version for colours)

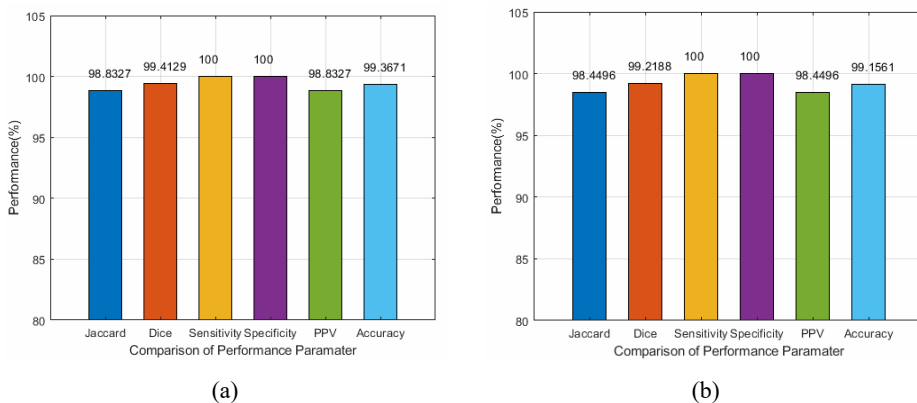
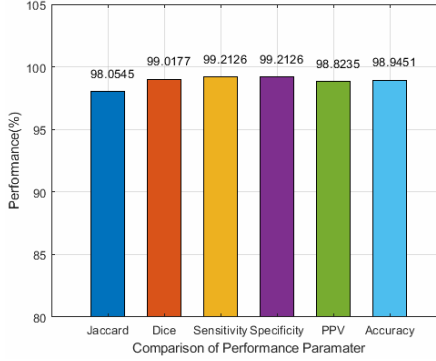


Figure 5 Performance analysis of the proposed DDVM model with (a) no input noise, (b) speckle noise of variance 0.01 and (c) Gaussian noise of variance 0.01 (continued) (see online version for colours)



(c)

4.2.1.1 Comparative analysis

The effectiveness of the proposed DDVM approach is evaluated by comparing its result with other existing techniques such as extreme learning machine (ELM) (Sharif et al., 2020), deep neural network (DNN) (Amin et al., 2018) and artificial neural network with multi-verse optimiser (ANN-MVO) (Elkorany and Elsharkawy, 2020) with regard to various performance parameters such as accuracy, sensitivity, specificity, Jaccard, Dice, and PPV. Table 3 compares the simulation results of the three different cases of the proposed DDVM approach with the ELM, DNN, and ANN-MVO techniques, and the results demonstrated that even under different noise effects the proposed scheme's tumour detection rate is better in every factor.

Table 3 Comparison of performance measures of the proposed DDVM model with the other models

<i>Method</i>	<i>Jaccard</i>	<i>Dice</i>	<i>Sensitivity</i>	<i>Specificity</i>	<i>PPV</i>
ELM (Sharif et al., 2020)	90	95.3	95	93	95.5
DNN (Amin et al., 2018)	90.4	95	95	95.2	97.2
ANN-MVO (Elkorany and Elsharkawy, 2020)	-	98.36	96.77	100	-
Proposed DDVM (no noise)	98.83	99.413	100	100	98.83
Proposed DDVM (speckle noise)	98.45	99.219	100	100	98.45
Proposed DDVM (Gaussian noise)	98.055	99.018	99.213	99.213	98.824

From Table 3, it is analysed that the value of Jaccard attained by the ELM, and DNN models are 90%, and 90.4% respectively, whereas in the proposed scheme this value is 98.833%, 98.45%, and 98.055% for no noise, speckle noise, and Gaussian noise case respectively. Similarly, the value of Dice attained by the ELM, DNN, and ANN-MVO models are 95.3%, 95%, and 98.36% respectively, whereas in the proposed scheme this value is 99.413%, 99.219%, and 99.018% for no noise, speckle noise, and Gaussian noise case respectively. Likewise, the value for sensitivity in the ELM and DNN models is 95%

in both the models, and for the ANN-MVO model is 96.77% and the value of specificity is 93%, 95.2%, and 100% respectively. On the other hand, the proposed DDVM model is performing far better than all the three models, specifically for sensitivity and specificity in all three scenarios of noise. The value of sensitivity and specificity for the proposed DDVM model without noise and with speckle noise is 100% and with Gaussian noise is 99.213%. Similarly, in the case of PPV the value attained by the ELM, and DNN models are 95.5% and 97.2% respectively, whereas in the proposed scheme this value is 98.833%, 98.45%, and 98.824% for no noise, speckle noise, and Gaussian noise case respectively. Thus, in all three scenarios, the proposed DDVM model outperforms the ELM, DNN, and ANN-MVO model and hence is more efficient.

In addition to this, the effectiveness of the proposed DDVM model is further validated by comparing its accuracy with the other models like ELM, DNN, ANN-MVO, adaptive neuro fuzzy inference system (ANFIS) (Selvapandian and Manivannan, 2018), and grey wolf optimiser and support vector machine (GWO-SVM) (Ahmed et al., 2019) models. The comparative analysis of the proposed DDVM model with the other models in terms of accuracy is given in Table 4.

Table 4 Comparison of accuracy of the proposed DDVM model with the other models

<i>Method</i>	<i>Accuracy</i>
ELM (Sharif et al., 2020)	96.5
DNN (Amin et al., 2018)	95.1
ANN-MVO (Elkorany and Elsharkawy, 2020)	97.62
ANFIS (Selvapandian and Manivannan, 2018)	98.5
GWO-SVM (Ahmed et al., 2019)	98.75
Proposed DDVM (no noise)	99.367
Proposed DDVM (speckle noise)	99.156
Proposed DDVM (Gaussian noise)	98.945

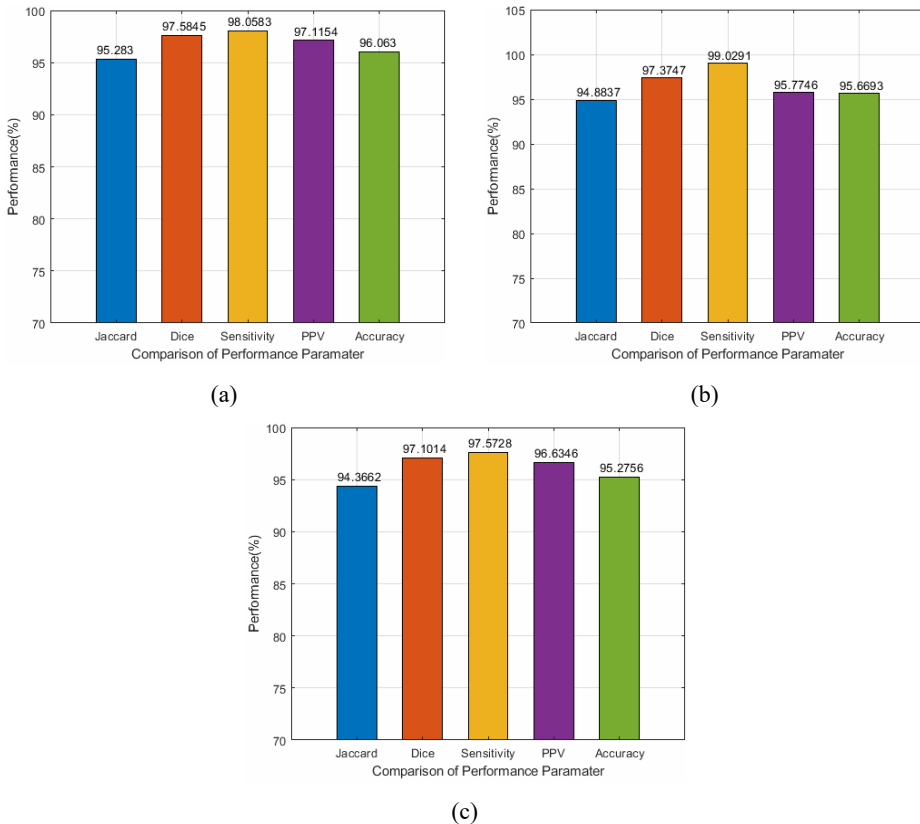
The significance of the given DDVM approach is analysed for accuracy in all three scenarios, i.e., with no noise, speckle noise, and Gaussian noise. After analysing Table 4, it is observed that the value of accuracy in the ELM, DNN, and ANN-MVO models are 96.5%, 95.1%, and 97.62% respectively. However, the value of accuracy is improved by around 1.1% in the conventional GWO-SVM model when compared with the ANN-MVO model, which is equal to 98.75%. Whereas, the value of accuracy in the proposed DDVM model in the normal case came out to be 99.3% which is more by around 0.617% than the traditional GWO-SVM model. In addition to this, when the speckle noise and Gaussian noise are added to the input data medical images, the value of accuracy is approximately 99.156% and 98.945% respectively. These results prove that the proposed DDVM model is producing more accurate results even when noise is added to the images and therefore is able to detect brain tumours more precisely.

4.2.2 Phase 2: classification of tumour type with LBP²Q featured SVM model

In the second phase of the proposed model, SVM is utilised that categorises the detected brain tumour into a specific class of tumour. Similar to phase 1, the proposed model is evaluated in terms of several quality determining factors which include Jaccard, Dice,

sensitivity, PPV, and accuracy for three different cases without noise and with speckle and Gaussian noise. The results obtained by the proposed LBP²Q featured SVM model for tumour type classification for the different performance parameters such as accuracy, sensitivity, Jaccard, Dice, and PPV are shown in Figure 6(a). The proposed LBP²Q featured SVM model resulted in an accuracy of 96.063%, sensitivity 98.058%, Jaccard 95.283%, Dice 97.585%, and PPV 97.115%. To further prove the robustness of the proposed algorithm to noise effect, we added speckle and Gaussian noise with variance 0.01 to the original MR image. The results obtained by the proposed LBP²Q featured SVM model for the different performance parameters with regard to different cases of the noise, i.e., speckle noise with variance 0.01, and Gaussian noise with variance 0.01 are shown in Figures 6(b) and 6(c), respectively. For the speckle noise case, the proposed LBP²Q featured SVM model resulted in an accuracy of 95.669%, sensitivity 99.029%, Jaccard 94.388%, Dice 97.375%, and PPV 95.775%. For the Gaussian noise case, the proposed LBP²Q featured SVM model resulted in an accuracy of 95.276%, sensitivity 97.573%, Jaccard 94.366%, Dice 97.101%, and PPV 96.635%. From the results, it is clear that the classification results remain firm to the noise type proving its robustness to the noise.

Figure 6 Performance analysis of the proposed LBP²Q featured SVM model with (a) no input noise, (b) speckle noise of variance 0.01 and (c) Gaussian noise of variance 0.01 (see online version for colours)



4.2.2.1 Comparative analysis

As stated in the previous section that before proposing the LBP²Q featured SVM model, three different scenarios normal SVM, SVM with LBP, and SVM with LPQ approach are designed and analysed. This section provides the comparative analysis of these techniques with the proposed LBP²Q featured SVM scheme to prove the effectiveness of the proposed scheme. Table 5 represents the values of various performance measures when no noise is applied to the input MRI image dataset. The results are achieved for normal SVM, SVM with LBP, SVM with LPQ, and proposed LBP²Q featured SVM.

Table 5 Comparison of performance measures of the proposed LBP²Q featured SVM model and the other models with no input noise

<i>Parameter</i>	<i>SVM</i>	<i>LBP-SVM</i>	<i>LPQ-SVM</i>	<i>Proposed LBP²Q featured SVM</i>
Jaccard	84.541	88.119	87.255	95.283
Dice	91.623	93.684	93.194	97.585
Sensitivity	81.126	96.739	96.739	98.058
PPV	88.384	90.816	89.899	97.115
Accuracy	87.402	90.551	89.764	96.063

After analysing the values given in Table 5, it is observed that the least performing model is SVM whose values came out to be 84.545%, 91.623%, 81.126%, 88.384%, and 87.402% for Jaccard, Dice, sensitivity, PPV, and accuracy respectively. However, the value of Jaccard came out to be 88.119% and 87.255% in LBP-SVM and LPQ-SVM respectively. While this value is 95.283% in the proposed LBP²Q featured SVM model when no input noise is added to images. Similarly, the values of Dice, sensitivity, PPV for traditional LBP-SVM and LPQ-SVM models are 93.684%, 96.739%, 90.816% and 93.194%, 96.739, 89.899% respectively. Whereas, the value of Dice, sensitivity, PPV in the proposed model came out to be 97.585%, 98.058% and 97.115% respectively. The accuracy achieved by the proposed model is 96.063% which is greater than the other three models. The proposed LBP²Q featured SVM model outperforms the other models in terms of all performance measures. There is an improvement of around 6% in accuracy in the proposed model when compared with the LBP-SVM model.

Next, the performance of the proposed model is analysed by adding speckle noise to the original dataset, in order to demonstrate and analyse what will be the impact on the classification system when any sort of noise will be there in the input dataset. Table 6 shows the values of various performance measures when speckle noise with variance 0.01 is added to the input MRI image dataset.

From Table 6, it is analysed that the values of Jaccard for the models normal SVM, LBP-SVM, and LPQ-SVM are 81.863%, 84.772%, and 84.5% respectively. While this value in the proposed model is 94.884%, which means that there is an improvement of around 13%, 10.11%, and 10.3% with respect to SVM, LBP-SVM, and LPQ-SVM models respectively. Similarly, the value of Dice in conventional SVM is 90.027%, followed by 91.758% in LBP-SVM and 91.599% in the LPQ-SVM model. However, the value of Dice in the proposed LBP²Q featured SVM model came out to be 97.375%, with an improvement of around 6%. The value of sensitivity for SVM, LBP-SVM, and LPQ-SVM are 79.981%, 93.296%, and 94.413%, respectively, whereas, in the proposed

model the value of sensitivity is 99.029%. The value of PPV for SVM, LBP-SVM, and LPQ-SVM are 86.979%, 90.27%, and 88.947%, respectively while this value is 95.775% in the proposed model. Furthermore, the value of accuracy achieved in normal SVM, LBP-SVM, and LPQ-SVM models are 85.443%, 88.189%, and 87.795% respectively. However, the value of accuracy for the proposed model is 95.669% which means that there is an improvement of around 7.4% when compared with the LBP-SVM model.

Table 6 Comparison of performance measures of the proposed LBP²Q featured SVM model and the other models with speckle noise

<i>Parameter</i>	<i>SVM</i>	<i>LBP-SVM</i>	<i>LPQ-SVM</i>	<i>Proposed LBP²Q featured SVM</i>
Jaccard	81.863	84.772	84.5	94.884
Dice	90.027	91.758	91.599	97.375
Sensitivity	79.981	93.296	94.413	99.029
PPV	86.979	90.27	88.947	95.775
Accuracy	85.433	88.189	87.795	95.669

Finally, the performance of the proposed model is analysed by adding Gaussian noise with variance 0.01 to the original dataset. Table 7 shows the values of various performance measures when Gaussian noise is added to the input MRI image dataset.

After analysing Table 7, it is observed that the value of Jaccard attained in normal SVM, LBP-SVM, and LPQ-SVM are 81.863%, 84.236%, and 86.207% respectively. While this value in the proposed model is 94.366% almost 8% more. Similarly, the value of Dice achieved in SVM, LBP-SVM, and LPQ-SVM are 90.027%, 91.444%, and 92.593% respectively. However, it is 97.101% in the proposed LBP²Q featured SVM scheme. Also, when the value of sensitivity and PPV are evaluated in SVM, LBP-SVM, and LPQ-SVM models, the value came out to be 80.84%, 88.83%; 93.443%, 89.529%, and 95.628%, 89.744% respectively. While the values of sensitivity and PPV for the proposed LBP²Q featured SVM model are 97.573%, and 96.635% respectively. Finally, the value of accuracy is evaluated which is 85.433%, 87.402%, and 88.976% in normal SVM, LBP-SVM, and LPQ-SVM models respectively, whereas, it came around 6.3% more in the proposed LBP²Q featured SVM model with 95.276% accuracy value.

Table 7 Comparison of performance measures of the proposed LBP²Q featured SVM model and the other models with Gaussian noise

<i>Parameter</i>	<i>SVM</i>	<i>LBP-SVM</i>	<i>LPQ-SVM</i>	<i>Proposed LBP²Q featured SVM</i>
Jaccard	81.863	84.236	86.207	94.366
Dice	90.027	91.444	92.593	97.101
Sensitivity	80.84	93.443	95.628	97.573
PPV	88.83	89.529	89.744	96.635
Accuracy	85.433	87.402	88.976	95.276

After analysing all the figures and tables, it is observed that the proposed model is providing more efficient and accurate results as compared to the traditional models in both phases whether it is about predicting the tumour presence or the type of tumour.

5 Conclusions

In this paper, an effective method is presented and designed for detecting and classifying tumours at early stages so that treatment can be done earlier to avoid human loss. The proposed model works in two phases, in the first phase, DDVM is developed that is based on CNN and Bi-LSTM for detecting brain tumours. In the second phase, LBP²Q featured SVM model is utilised for classifying the type of tumours. The effectiveness of the proposed model is validated in MATLAB software. The simulated outcomes are determined and compared with different state-of-art methods in terms of Jaccard, dice, sensitivity, specificity, PPV, and accuracy in normal cases and when noise is added to input images in both phases. The Dice value of the proposed DDVM model is improved by around 1.053% in the normal case on comparing it with the best out of the traditional ANN-MVO model. While, when speckle noise and Gaussian noise are added to input data images, the performance of the proposed DDVM is still far better with an improvement of 0.859% and 0.658% in Dice value than the standard ANN-MVO model. Moreover, the value of sensitivity is 2.44% more than the standard ANN-MVO model when Gaussian noise is added to the input dataset. Furthermore, the value of accuracy achieved in the proposed DDVM model is improved by around 0.6% in the normal case than the conventional GWO-SVM model. Also, the value of accuracy is more by around 0.4% and 0.1% when speckle and Gaussian noise is added to input images. The proposed model outperforms the traditional models in the second phase as well, in which the value of Jaccard, Dice, sensitivity, PPV, and accuracy is improved by 7.15%, 3.9%, 1.3%, 6.2%, and 5.5% than standard LBP-SVM model in normal case. Furthermore, when the speckle noise and Gaussian noise are added to images, the value of accuracy is improved by 7.8% and 6.3% when compared with the traditional LPQ-SVM model. Hence, in both phases, the proposed model is performing more efficiently and effectively in detecting and classifying tumours and can be adapted for future brain tumour classification models. With scalability in the available dataset, the solution can be implemented in real-time applications and can be further enhanced in the future for dynamic datasets. Considering the distributed database system and cloud storage of tumour image datasets the outcome of the solution can be directly implemented for the real-time IoT-based tumour diagnosis and recommendation system for the doctors or the medical staff. Although the current method is delivering expected results in tests, one drawback that may develop is due to the manifest in classification model, which might overfit the training dataset and lead to poor classification on the whole dataset. This issue might be taken into account in future models when designing systems for health-care applications.

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