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ORIGINAL RESEARCH

Smart Investigations into the Development of an Effective Computer-Assisted Diagnosis System for CT Scan Brain Depictions

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Abstract

Recent advances in medical image analysis on computers are anticipated to help radiologists and other healthcare workers with numerous diagnostic tasks including medical image interpretation. Accurate diagnosis and/or assessment of a condition in medical imaging relies on both the quality of the acquired images and the quality of the interpretation of those images. To accomplish this, large amounts of picture data and medical records must be combined. Computer-aided diagnosis (CAD) systems have been developed in response to a lack of accuracy to boost the radiologist's productivity and precision in their interpretations. Given the importance of computerised tomography (CT) imaging in this field, we have made an effort in our research to examine CT scan brain images by applying a number of feature extraction and selection techniques, as well as classification techniques, to diagnose different types of brain disorders. Brain CT scans are analysed here and classified as either normal, benign tumours, or malignant tumours. Finding the best characteristics to use in a classification system is called "feature selection," and it requires sifting through a vast amount of extracted features to locate the most relevant ones. To evaluate the efficacy of the implemented classifiers, we used measures of accuracy, specificity, sensitivity, positive prediction value, and negative prediction value. Traditional classifiers are also examined alongside the suggested method's results. The proposed decision support systems outperform the standard classifiers in terms of accuracy. An FSVM is generated by applying the RBF kernel function to this dataset. This method is compared to the support vector machine (SVM) and the multi-layer perceptron neural network (MLPNN) in terms of accuracy, sensitivity, and specificity of the classifiers they produce. Accuracy (96.25%), sensitivity (96.67%), and specificity (95.83%) are all significantly higher when using the proposed method as compared to the control methods.

Keywords CAD · SVM · Fuzzy SVM · CT · PPV · NPV

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Introduction

When it comes to cancer-related deaths, brain tumours rank second among men and sixth among women. In the USA, around 19,000 people each year are diagnosed with a primary brain tumour. According to the World Health Organization (WHO), brain tumours are a primary cause of death around the world, with no exceptions for either developed or developing nations. About 2,95,986 people in the USA were diagnosed with primary benign and primary malignant brain tumours between 2004 and 2008, according to data from the Central Brain Tumor Registry (CBTRUS) [1]. Malignant tumours made up just 34.4% of all diagnoses, whereas benign tumours made up 65.5%.

CBTRUS reports that between 2006 and 2010, the average annual incidence rate of primary malignant and benign brain tumours was 21.03, when adjusted for age. The rate is greater for women than for men (22.79 vs. 19.11), for Whites than for Blacks (21.13 vs. 20.54), and for non-Hispanics than for Hispanics (21.30 versus 19.77). Overall, the incidence rate of primary malignant brain tumours was 7.27 per 100,000 people per year after adjusting for age.

Incidence rates of benign brain tumours were 13.77 per 100,000 people per year, when adjusted for age. The rate of newly diagnosed primary malignant and benign brain tumours in children and adolescents aged 0–19 years was 5.26 per 100,000 in the years 2006–2010. Between 2006 and 2010, 68,184 patients with a primary malignant tumour passed away. The relative 5-year survival rate for patients with a malignant tumour diagnosis was 33.8%. Patients between the ages of 0 and 19 years had a 73% survival rate, whereas those aged 70 years and up only had a 5.8% survival rate [2].

The incidence of primary brain tumours in India is 3.4% for males and 1.2% for females, according to data from the National Cancer Registry Program. In India, less than 1% of new cancer cases are identified each year, according to this study.

However, primary brain tumours have been increasing in frequency during the past decade. Primary brain tumours are uncommon in children and young adults, although early identification improves survival rates. For this reason, it is crucial to discover and treat brain tumours as soon as possible to increase the survival rate of cancer patients. The use of medical imaging has greatly advanced cancer diagnosis and treatment. Automatic tumour detection and categorisation in medical imaging is a high-stakes endeavour due to the potential for patient death [3].

Computer tomography, magnetic resonance imaging, positron emission tomography, and other modern medical imaging techniques have all made great strides in detecting brain disorders. Yet, CT scan brain images, with their low contrast and variances in the kind of tissues, are the most challenging medical images to analyse among these methods [4].

There is some evidence that double-reading medical photographs can increase the success rate of finding tumours, but the added cost is too high to make this a practical option. Because of this, a lot of effort goes into creating reliable software that radiologists may utilise to make accurate diagnoses. Although obtaining a high level of accuracy is difficult, equipping radiologists with some form of computer software may help reduce the influence of human error [5]. A CAD system is desired to aid in the interpretation of medical images, and the radiologist will frequently refer to the CAD system's output as a “second opinion” before making a final call.

The most recent CT equipment makes it possible to compile a study’s worth of data into a single file (known as volumetric CT study). Thanks to the processing power of modern computers, the oncologist may quickly reconstruct the patient’s “slices” in any plane the patient requests, with any slice thickness to help make a more accurate diagnosis [6]. The CT scan machine is depicted in Fig. 1.

Computer-Aided Diagnosis

Physiologists can typically use imaging techniques to detect brain abnormalities. Since radiologists deal with a large volume of images every day, even those with extensive training and experience may make mistakes while interpreting the scans. As a result, a specialised CAD system is developed to aid radiologists in the interpretation of medical pictures and to serve as a secondary observer in the final decision-making process. In certain clinical situations, radiologists may choose to either concur with the computer's findings or reject them outright [7]. In circumstances where radiologists have less certainty, however, the computer output is intended to help with the final call. Of course, this enhancement can only be implemented if the computer result is accurate. The greater the computer's performance, the greater is the total impact on the final diagnosis. There is no requirement that the machine perform at or above the level of human radiologists. The potential improvement comes from integrating the knowledge of the radiologist with the power of the computer. These cumulative advantages have led to widespread adoption of the CAD in real-world clinical settings.

Brain Tumour Types

There are two main categories of brain cancers, and they are called primary tumours and secondary tumours. Brain tumours can be classified as either primary (originating in the brain) or secondary (metastatic) depending on how they cross the blood–brain barrier. Primary brain tumours, also

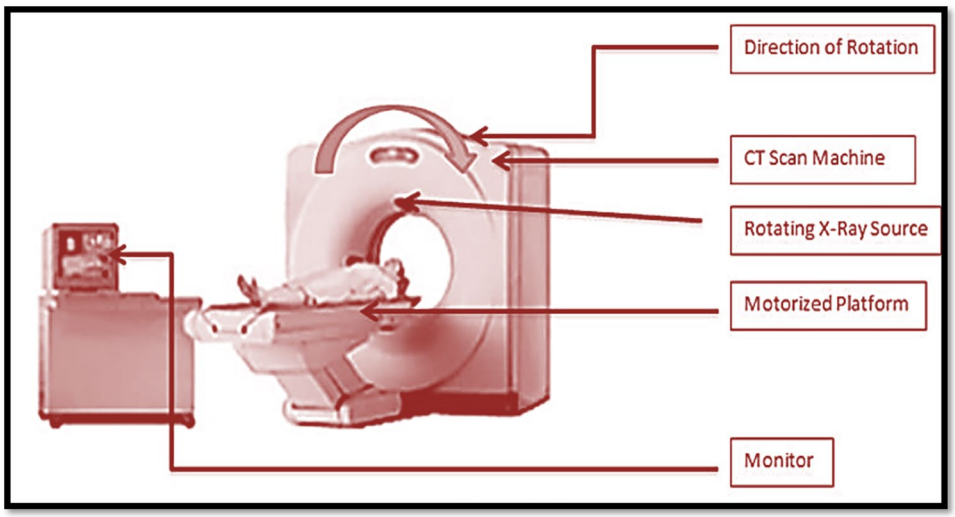

Fig. 1 CT scan machine

known as neoplasms of the brain, can be classified as benign or malignant depending on whether or not they originate from neurons (brain cells) or neuro-epithelial cells (support cells) [8].

Noncancerous, or benign, tumours are not aggressive and do not spread to neighbouring tissues or have unclear borders. Due to the similarities between these cells and healthy ones, the diagnosis will be difficult. It is important to remember that over 40% of primary brain tumours are actually benign. Depending on the size and location of the benign tumour, either radiation therapy or surgical removal treatment is done.

Tumours that are cancerous, or malignant, are extremely dangerous because they are aggressive and invasive. Brain malignancies, in contrast to many other malignant tumours (such as those of the liver, breast, lung), tend to remain contained within their original site. Surgical excision of a malignant tumour in the brain is highly risky due to the fragility of the surrounding brain tissue. About 20% of primary brain tumours are glioblastoma multi-forme (grade IV astrocytomas), the most prevalent type of malignant primary brain tumour.

Related Work Done

In this study, we break down the CAD system's implementation into three distinct phases: pre-processing; feature extraction and selection; and classification or DSS. In the following paragraphs, we talk about a few of the methods we used [9].

Increasing the effectiveness, decreasing the complexity, and shortening the computation time of the CAD algorithms all depend on proper pre-processing of pictures. CT scan image quality is typically affected by imaging sequences and/or patient cooperation. Therefore, the range of pixel values, the amount of noise, and the overall background level are highly variable [10].

For this reason, pre-processing is done to improve the image quality, which can be done by boosting the contrast, eliminating the background tissue, or decreasing the noise. Researchers have tried both locally and globally based techniques for contrast enhancement, such as area thresholding, density-weighted contrast enhancement and segmentation, and histogram equalisation. Non-linear methods such as median filtering, edge-preserving smoothing, half-neighbourhood, and directional smoothing are among the noise-reduction strategies [11].

To isolate the area of interest (ROI) for further abnormality analysis, the image must be pre-processed. The segmented part is then analysed further to cut down on computational time and simplify the classifier's structure. Grey level-based and textural feature-based approaches, among others have been presented and applied for segmenting suspicious area from the complete medical image. The techniques of amplitude segmentation using histogram features, edge-based segmentation, and region-based segmentation all fall under the umbrella of grey level-based segmentation. Since MR and CT scan pictures are frequently utilised for brain imaging, researchers have focused a great deal of attention on developing effective methods for segmenting these images [12]. It involves segmenting the brain into its component parts (grey matter, white matter, and cerebrospinal fluid). Intensity-based segmentation methods, such as threshold based, region based, deformable model based, and neural network based, predominate among the options for segmenting CT and MR images.

Feature analysis and extraction is a crucial part of any CAD system.

The CD system does not have a "royal route" for extracting features because the techniques used to do so vary from object to object in each medical image. The main problem with feature extraction is making sure the features accurately reflect tumour traits [13].

Using these characteristics, aberrant tissues can be distinguished from healthy ones. Comparing the difference between feature values for objects in different categories (interclass variability) with the difference in feature values for objects within the same category (intraclass variability) is crucial for the accuracy and efficiency of the classification process. Effective and relevant features for detecting certain objects (tumours) should be picked after taking the appropriate time and discussion with the radiologist [14].

As a result, many different feature extraction approaches have been developed for use in neuro-radiological CAD systems to characterise various lesions and disorders. It is possible to employ smoothness, roughness, regularity, resolution, contrast, mean, and other qualities specified by texture in image feature extraction, which is why texture is the most valuable description property of an image [15]. The spatial distribution of pixel intensities is what defines texture information.

Since it is challenging to characterise the tissues present in medical images based on shape or intensity-level information, several researchers have turned to texture feature extraction algorithms. Markov random fields, wavelet-based filtering, run length matrices, co-occurrence matrices, and autoregressive modelling are just some of the methods that can be used to analyse the characterisation of texture in medical images. The process of medical image diagnosis has involved the use of a wide variety of texture feature techniques; however, the spatial grey-level dependence (SGLD) matrix and Gabor filtering approaches are particularly well received for texture feature analysis due to their demonstrated efficacy across a wide range of applications and image types [16].

For supervised discretisation, the authors provide a straightforward approach that uses a one-rule algorithm (1R). This technique takes into account a single feature at a time, first sorting the values of that feature, and then looking for interval boundaries where one class is overrepresented. To prevent intervals with a small number of 17, every interval produced using this method should have a certain minimum amount of instances. Researchers evaluated various ranking algorithms and demonstrated that the ranking indices selected for each algorithm had an effect on the classifiers' performance [17–20].

The authors utilised a heuristic approach to minimal entropy to discretise the numerical characteristics. Using the class entropy of potential partitions, the algorithm chooses a cut point for discretisation.

Multiple intervals for the feature can be generated by using the method iteratively on the two intervals produced by the preceding split until the stopping criteria are met. The problem of converting numbers into words is one that has to be tackled [21–24]. The benefits of employing the discretisation approach are outlined, and the term's definition is made clearer, in this study.

The CAD system's most crucial phase is the categorisation phase. The classifier takes an image as input and outputs a classification decision (normal or pathological tissue). The feature vectors of the training photos are used to train the classifier and teach it to correctly assign labels to new images. Supervised learning is a type of machine learning. Because they are built on the clinical truth and evidence accumulated for the specific condition, most CAD systems use the supervised learning method [25–28]. A large enough training set is used to create the classifier, which in turn improves the CAD system's efficiency, accuracy, and resilience.

When it comes to the early detection of Alzheimer's disease using emission computed tomography images, the authors proposed a CAD that combines continuous attribute discretisation and association rule mining [29]. The normal pattern of a picture is fully characterised by isolating the regions of interest (ROI) and feeding them into an association rule (AR)—mining process with photos of control subjects. To acquire the rules with the highest predictive power at each discretisation level, the minimum values of support and confidence are fixed to the maximum values. Finally, classification is accomplished by contrasting the total number of ARs confirmed by each participant [30–32]. Single-photon emission computed tomography (SPECT) and positron emission tomography (PET) image databases are used to assess the effectiveness of the suggested method in the diagnosis of Alzheimer's disease. Accuracies of 95% (for SPECT) and 92% (for MRI) were achieved (for PET).

The Proposed Work

This study details the planning, execution, and assessment of a computer-aided decision support system tailored specifically to brain tumour imaging in an effort to enhance diagnostic precision and workflow. Brain tumours were classified as either benign or malignant using a fuzzy support vector machine (FSVM)-based classification approach. Results from our experiments suggest that our solution outperforms the status quo.

Previous studies showed that a support vector machine (SVM) approach outperformed other automatic diagnostic systems in terms of accuracy. Researchers have been paying a lot of attention to SVM-based classification and regression methods as a result. However, due to overfitting, some input

samples may not be exactly allocated to one class, and the SVM classifier is therefore particularly sensitive to outliers or disturbances in the training sample. The fuzzy support vector machine overcomes these deficiencies.

Multiple studies have shown that fuzzy SVM mitigates the impact of data sample outliers and noise. However, fuzzy SVM is not the only one compatible with data points that have unmodelled features. Consequently, an adaptable model is created by merging the ideas of support vector machines and combining statistical logistic regression, vector machines, and fuzzy logic. Consequently, we suggest CT brain image diagnosis using a fuzzy support vector machine classifier makes ANN- and SVM-based classifiers functional again. Figure 2 employs a fuzzy support vector machine (SVM) based classifier, and hence the name of the proposed system.

Pre-processing and Segmentation

Pre-processing aims to boost the quality of the brain pictures by getting rid of the noisy, incomplete, and inconsistent data. By using a median filter, we can clean up the photos and make them look better than they otherwise would. To improve contrast information and verify overall intensity distribution in brain soft tissue pictures, the histogram equalisation method is utilised. In this study, we combined Mumford–Shah segmentation techniques with the level set method to create an active contour model. This strategy does not rely on an edge function to force the advancing curve to halt at the specified boundary. In this technique, the locations of borders are very successfully recognised and kept, even if the initial image is very noisy. This technique is useful for the detection of objects whose edges are not always sharp or defined by a gradient. It requires only a single starting curve to automatically detect the internal features. The starting curve need not be drawn around the items to be recognised, and can instead be drawn anywhere in the image. It is now possible to further process the image after isolating the suspicious region. They used a number of numerical results to verify their model. Using the aforementioned technique, we segment the photos to isolate the potentially harmful regions of interest. The segmented parts of the photos are taken into account for the next step of the analysis.

Feature Abstraction

Computer-aided diagnosis (CAD) systems rely heavily on feature analysis and extraction for tumour detection and categorisation. Malignant tumours can be distinguished from benign ones by analysing their features to determine if they have any of the aforementioned characteristics. This is the primary concern in feature analysis. In this study, we create feature vectors by extracting six texture features from photographs. Features are derived from the GLCM at 1, 2 distances along the 0°, 45°, 90°, and 135° axes. Each image is broken down into 20 8×8 matrices. The following six texture features are computed for each GLCM. These features are variance, homogeneity, correlation, energy, entropy, inverse difference moment.

Feature Selection

Some of the aforementioned characteristics are highly linked to one another. Selecting a subset of the original characteristics according to some criterion is done through a feature selection technique to boost the system's performance.

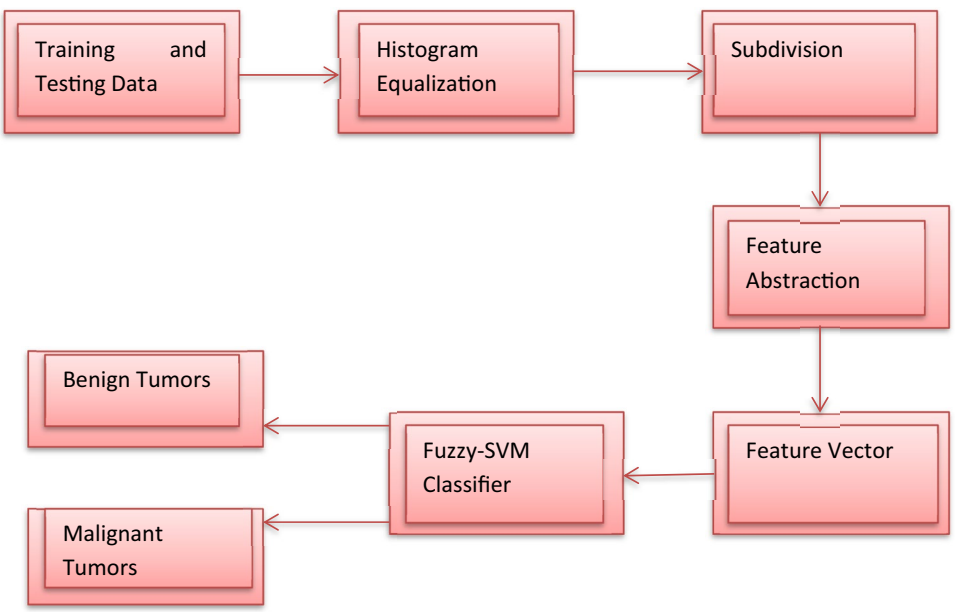

Fig. 2 The proposed block diagram for CAD fuzzy SVM

There is a lot of redundant information in data, and feature selection algorithms can pick a subset of features with fewer pieces that still retains the useful information in the original data. So, feature selection is the process of zeroing in on features that are less correlated with one another and more strongly linked to the decision classes.

Classification Using Fuzzy SVM

In addition to classifying linear data, SVM can also be used to categorise non-linear data. Let's start with binary data classification based on linear dissimilarities. Assume that the input samples can be linearly separated, and that there is a training set D with L labelled samples $(x_1, y_1),\ldots,(x_L, y_L)$, where x_i RN belongs to either of two classes and is given a label $y_i - 1$, 1, for $I = 1,\ldots,L$. The goal of this approach is to locate the hyperplane that maximally separates two sets of data, i.e. the hyperplane that provides the largest feasible distance between the classes and lies farthest from the two convex hulls. For each class, the convex hulls are constructed by joining together the exemplars used during training. Support Vectors are the training data set that lies closest to the hyperplane. The results of an SVM algorithm applied to a binary problem with linearly separable features are illustrated in Fig. 3. In this case, the ideal separating hyperplane is the one that maximises the distance between the support vectors of the two groups.

Let us pretend, as illustrated in Fig. 4, that the input samples are not linearly separable. To address this issue, support vector machines (SVMs) use a mapping $z = (x)$ to convert input samples from X-dimensional input space to Z-dimensional feature space, and then search for the optimal separating hyperplane that maximises the margin between two classes by dividing the newly transformed data (x_i), y_i. The use of kernel functions has enabled this.

While SVM is a robust method for resolving classification issues, it does have significant restrictions. Each point in the training set that is of the same class contributes equally to the

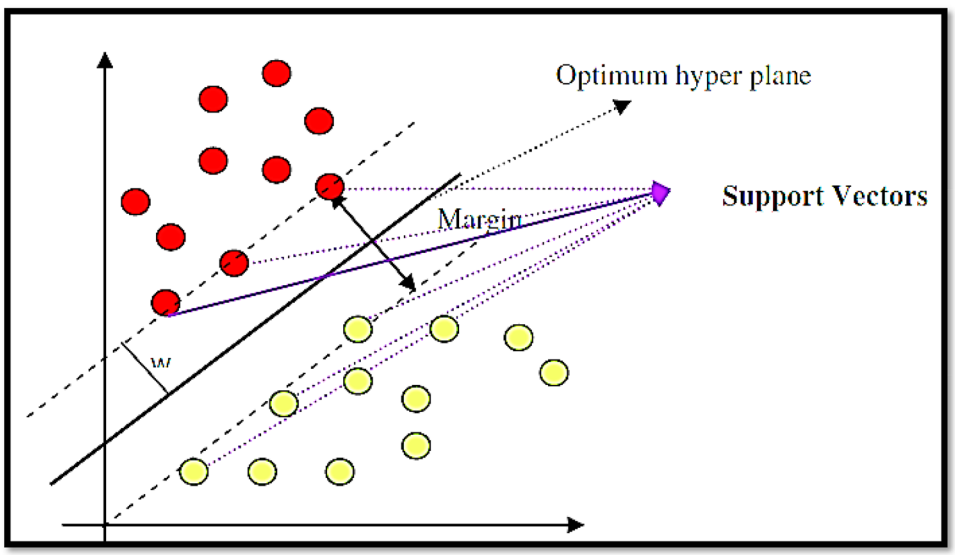

Fig. 3 Outcome of an SVM algorithm for a linearly separable binary problem

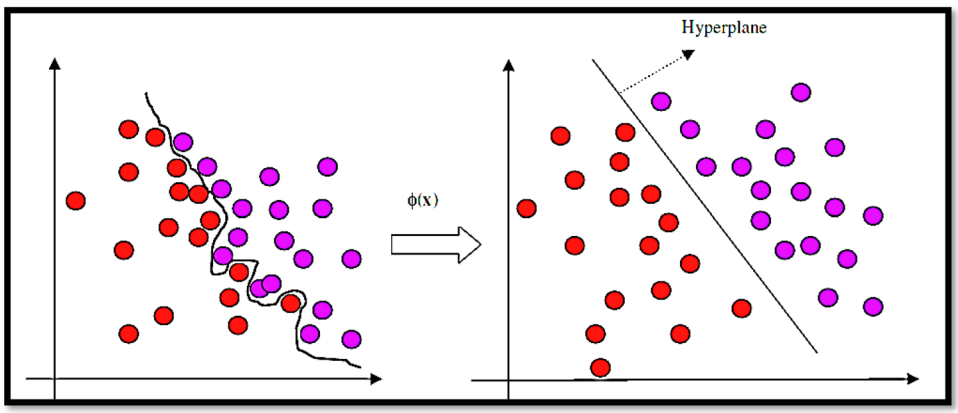

Fig. 4 Non-linear data into linear data transformation

decision surface in SVM. However, in many practical contexts, some training points are more crucial than others in the context of the classification problem. The system may fail to correctly categorise test data if, for example, 80% of training sample xi belongs to class + 1 and 20% to class − 1, or if there is noise or outliers present in the training samples. Each input sample (x_i, y_i) is assigned a membership mi in the fuzzy theory, with 0 mi 1. An outlier is a data item in the training set that is given a low membership to reduce the impact it has on the error term as a whole. To lessen the weight given to less significant data points, this fuzzy SVM variant softens the penalty term. Fuzzy Support Vector Machines is a new concept that combines SVM with fuzzy membership (FSVM).

Performance Evaluation

We calculate the suggested system's positive predictive value, negative predictive value, sensitivity, and specificity to gauge its efficacy. The overall accuracy of the proposed system is measured by how well it can make proper diagnoses from the images provided. The sensitivity of a system is defined as its propensity to identify instances that are true positives. The ability to identify "normal" or "negative" cases is what we mean by "specificity." The PPV measures the accuracy with which a test's positive results are indicative of a true positive, while the NPV does the same thing for negative results. Details of the procedures are provided below:

$$\text{Senstivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} X100, \tag{1}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} X100, \tag{2}$$

$$\text{Accuracy} = \frac{\text{TN} + \text{TP}}{\text{Total data Sample}} X100, \tag{3}$$

$$\text{Positive Predicitve Value} = \frac{\text{TP}}{\text{TP} + \text{FP}}, \tag{4}$$

$$\text{Negative Predictive Value} = \frac{\text{TN}}{\text{TN} + \text{FN}}, \tag{5}$$

where TP, TN, FP, and FN stand for true positive (correctly classifying an abnormal case), true negative (correctly classifying a normal case), false positive (correctly classifying a normal case as abnormal), and false negative (incorrectly classifying an abnormal case as normal).

Result and Discussion

There are a total of 400 CT scan brain images in the collection, 200 from each of five different categories (benign and malignant). Training set images total 160 (40% of dataset; 80 photos per category); test set images total 240 (60% of dataset; 120 images per category). With the aid of a radiologist, a single image is chosen for a single patient.

MATLAB 7.6 is used to implement the CAD system for the requested work. Histogram equalisation is used to increase contrast in CT scan brain pictures, and median filtering is used to decrease noise. The aberrant tissue development has been identified and segmented from the image using active contours based approaches before feature extraction.

The image is segmented to isolate the suspicious region for further study. Grey-level co-occurrence matrices are created for every segmented image in one and two different distances along the 0°, 45°, 90°, and 135° axes (Table 1).

During the test phase, the best FSVM model (classifier) developed during training is applied to the diagnostic image using the pre-processing and feature extraction approaches used during training. The image is classified as benign or malignant based on the classifier's output. The FSVM's results are measured against those of the more conventional support vector machine (SVM) and multi-layer perceptron neural network methods (MLPNN). In this case, an RBF kernel function is used to create the SVM, and a quadratic programming-based training technique is used to optimise the model.

MLPNNs have an input layer of 18 neurons, a single hidden layer of 15 neurons, and an output layer of 2 neurons.

Table 1 Features for direction 0°, 45°, 90°, and 135°

Features	Direction ($d=1$)				Direction ($d=2$)			
	0°	45°	90°	135°	0°	45°	90°	135°
Correlation	0.9764	0.9562	0.9671	0.9545	0.9514	0.8996	0.9257	0.8941
Energy	0.0989	0.0899	0.0941	0.0897	0.079	0.0725	0.0823	0.0735
Entropy	2.7096	2.74681	2.7088	2.7391	2.8928	3.0259	2.8757	3.0204
Homogeneity	0.9165	0.8875	0.9423	0.8841	0.8637	0.8265	0.8492	0.8106
Variance	25.712	25.642	25.565	25.62	25.589	25.7671	25.647	25.639
Inv. Diff. moment	0.9948	0.9959	0.9924	0.9839	0.9962	0.9871	0.9852	0.9880

Table 2 Confusion matrix of classifiers fuzzy SVM, SVM, and MLPNN (120 images)

Classifier	Type of tumour	Correctly classified images	Classification rate (%)
FUZZY SVM	Benign	116	96.83
	Malignant	115	95.67
SVM	Benign	106	86.00
	Malignant	100	82.67
MLPNN	Benign	99	81.50
	Malignant	96	79.33

This network was educated with a sigmoidal activation function and the back propagation technique. As seen in Table 2, FSVM, SVM, and MLPNN all have their own unique confusion matrices (Figs. 5, 6).

As a general rule, CAD programmes will attempt to draw attention to anything that looks fishy. A perfect CAD system would be both sensitive (e.g. it would correctly identify all malignant tumours) and specific (e.g. it would correctly identify only benign tumours) (e.g. all benign tumours are not identified as malignant tumours). In the current state of affairs, no CAD system can detect 100% of pathogenic alterations. A better CAD system would be one with higher sensitivity, specificity, positive predictive value, and negative predictive value. To this end, we experimented with various methods to improve our CAD system for data processing, and rated them according to the following criteria: precision, recall, recurrence, and false-positive rates. The suggested system's overall accuracy is measured by how well it can make diagnoses from CT scans of the brain (benign or malignant). The percentage of true-positive cases (malignant) that are accurately recognised is the measure of sensitivity (the percentage of sick people who are correctly identified as having malignant tumours). The rate of false-positive diagnoses (malignant) is directly correlated to a test's specificity (the percentage of people who are correctly identified as having benign tumours). If a test comes back positive, how likely

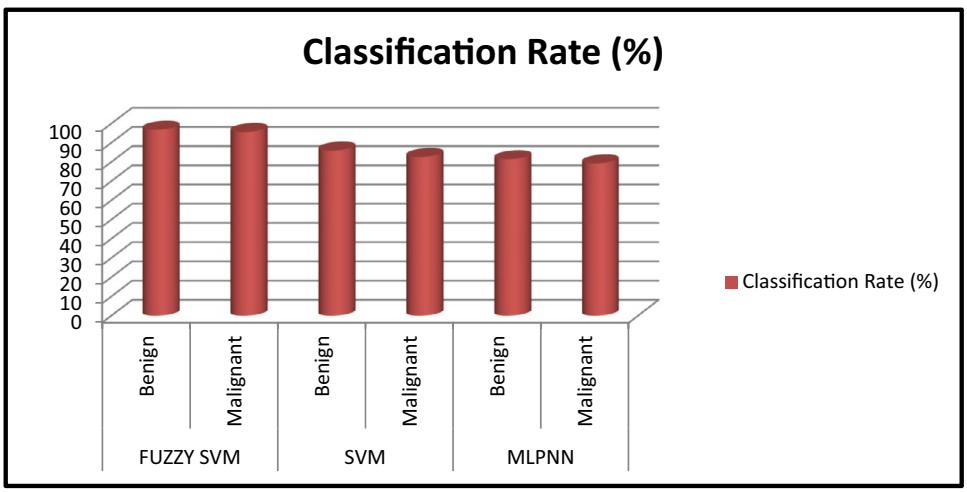

Fig. 5 Classification rate comparison of fuzzy SVM with the existing approach

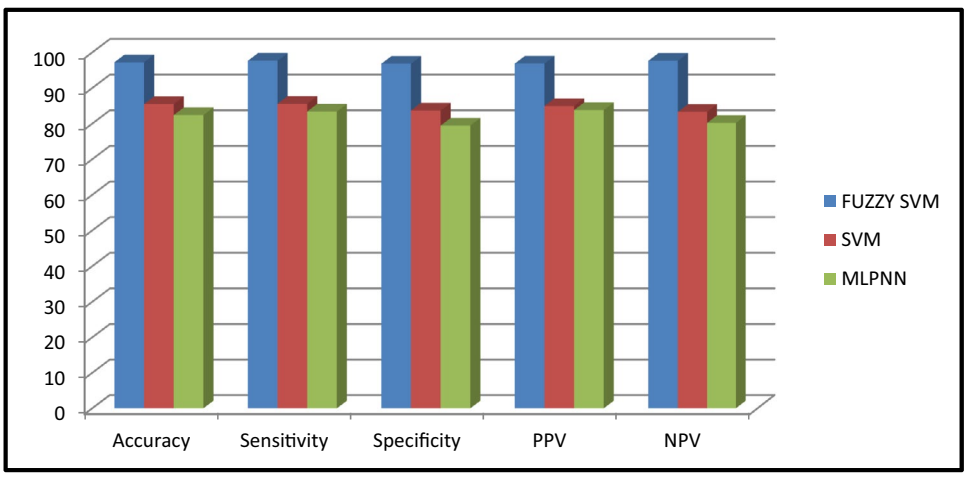

Fig. 6 Performances Comparison of FUZZY-SVM, SVM and MLPNN

is it that the disease is actually present? This is what we mean by the PPV, or predictive positive value. If a test comes back negative for an illness, that raises the likelihood that the disease is not present, a concept known as the "negative predictive value" (NPV).

Table 3 displays the accuracies, sensitivities, specificities, and positive and negative predictive values. In addition, it displays a comparison of fuzzy SVM, SVM, and MLPNN in terms of the aforementioned performance indicators. It is accepted that the performance of a CAD system based on fuzzy SVM is superior to that of the other two methods.

The adequacy of the proposed system can be measured using receiver operating characteristic (ROC) curves. Different classifiers' ROC curve performance is displayed in Fig. 7.

ROC curves are generated for the purposes of determining specificity and sensitivity by utilising test samples that are chosen at random from the whole picture set (40, 50, 60, 70, 80, 90, and 100). The area under the ROC curve achieved by fuzzy SVM (0.972) is larger than that achieved by SVM (0.889) and MLPNN (0.589). (0.912).

Table 3 Performances comparison of fuzzy SVM, SVM, and MLPNN

Classifiers	Accuracy	Sensitivity	Specificity	PPV	NPV
Fuzzy SVM	97.25	97.67	96.83	96.87	97.64
SVM	85.49	85.58	83.70	84.98	83.30
MLPNN	82.40	83.41	79.46	83.82	80.20

Conclusion and Future Scope

Conclusion

In this research work, we discuss the design and implementation of a computer-aided diagnosis system for brain CT scan pictures. There are three types of CT scans of the brain: normal, benign, and malignant. We have broken down the process of solving our problem into three steps. 1. Methods for extracting and choosing features third, a decision-making aid or system. In feature extraction, several texture features are retrieved from the training images and used for subsequent analysis. These features can be Haralick texture features, Gabor wavelet features, or histogram-based texture features. To construct a reliable and effective classification system, it is necessary to first discover an appropriate subset of features from a huge set of extracted characteristics. Finding the most relevant features for building a powerful classifier that can accurately categorise unknown data is the focus of this strategy. To train the fuzzy SVM-based classifier, we use a logistic regression approach to assign each feature vector in the training set a fuzzy membership. When the RBF kernel function is applied to this dataset, an FSVM is produced. Classifier accuracy, sensitivity, and specificity are evaluated between this method and the support vector machine (SVM) and the multi-layer perceptron neural network (MLPNN) used in previous work. The results show that the proposed method is superior to the control methods in terms of accuracy (96.25%), sensitivity (96.67%), and specificity (95.83%) in aiding decision making.

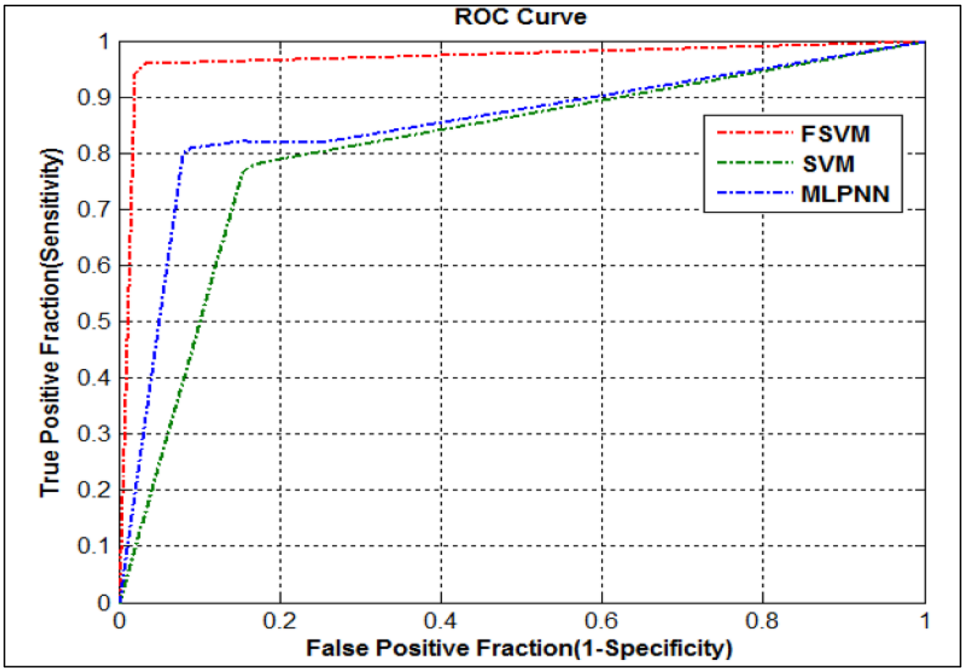

Fig. 7 Performance analysis using the ROC curve

Future Scope

To improve the decision support systems for CT scan brain pictures, researchers may focus their efforts in the future on extracting characteristics other than texture features. CT scans of the brain could benefit from a novel segmentation strategy.

In the future, studies may take into account the total amount of time a CAD system takes to process on a computer as a performance metric. The classifiers can be further tuned for faster execution and deployed across a cluster of computers to run in parallel. The effects of different factors can be investigated in the present work, which can be used and tested for other picture kinds and other body parts of the images (such liver, kidney).

For this thesis to be used as a clinical tool for doctors to diagnose and differentiate between different forms of brain tumours, the methodologies and procedures applied within it must be combined in a simple and user-friendly interface.

Declarations

Conflict of Interest The authors declare that there is no conflict of interest regarding the publication of this paper.

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