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A Combined Approach for Multiclass Brain Tumor Detection and Classification

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Abstract- **Brain tumor is a threat to human lives and is constantly growing. Early detection could reduce/minimized life threats. Currently, researchers are employing various machine vision-based techniques for brain tumor detection. This study focuses on a combined approach incorporating machine learning and deep learning for brain tumor detection. The initial step of the research was feature extraction which was acquired via a convolution neural network (Alex Net) and subsequently classification which was achieved via an ensemble classifier. The developed method is a non-invasive, contactless machine -vision based system for early diagnosing/detection of brain tumor. Various statistical variables such as mean, median, mode, skewness, and kurtosis to develop a multiclass ensemble classification model. The results exhibit that proposed method is 95.547% efficient compared to other methods.**

Index Terms-- **Biomedical Engineering, Artificial Intelligence, Clinical Image Processing, and Deep Learning.**

I. INTRODUCTION

With billions of cells and neurons working together, the brain is one of the most sophisticated organs in the human body. When cells divide uncontrollably, they lead to an abnormal clump of cells around or inside the brain, which is known as a brain tumour. This group of cells has the potential to disrupt regular brain functioning and destroy healthy cells. Brain tumours are a major cause of cancer-related morbidity and mortality worldwide, with an annual incidence of 4–5 per 100,000 cases, accounting for 2% of all cancer fatalities. In Pakistan, around 150 000 new instances of cancer are diagnosed each year, with 60–80 % mortality rates [1].

Normally, more than a hundred different types of brain tumours could be classified based on their location and progression. Based on their progression, clinical experts also classified brain tumour's as Grade I, Grade II, Grade III, and Grade IV. The two most common types of brain cancer are benign and malignant, with the former having some strict and non-existent uniformity and the latter having no organized and consistent uniformity. Tumours could be detected using a variety of imaging techniques. Magnetic Resonance Imaging (MRI) is a complex medical imaging method that is an effective tool for examining the human brain. The wealth of information provided by MR imaging of soft tissue and anatomy has greatly enhanced the accuracy of brain pathology diagnosis and therapy. The most significant benefit of magnetic resonance imaging is that it is non-invasive. Tracking the size of a brain tumour as it reacts to treatment is an important application of MRI data. Magnetic Resonance Imaging (MRI) technology is a medical imaging technique that is employed to visualize the inside structure of the body and produce high-quality images [2]. Meningioma, glioma, and pituitary tumour's, for example, are all characterized in different ways. The size, form, and other characteristics of a tumour are employed to categorize it. MRI (Magnetic Resonance Imaging) is the most advanced tool for generating high-quality images of tumour-containing regions in the field of medical imaging. The popularity of MRI stems from the scan's lack of ionizing radiation and the ability to generate a variety of pictures with high sensitivity tissue resolution and discrete imaging boundaries as contrast-enhancing agents. The three types of brain tumours are as follows: The meningioma tumour develops on the lining of the brain, covering the muscles, spinal cord, and the human skull. The majority of meningioma tumours are benign. Gliomas are another common type of brain tumour in which 80% of the cells are cancerous. The pituitary gland, on the other hand, could generate a pituitary tumour, which governs hormones and activities in the body and could result in lifelong hormonal shortage as well as visual loss. If these are not recognized and diagnosed effectively over time, human mortality may occur. Brain tumours could be identified and classified quickly and without the need for human interaction. The usage of Computer-Aided Technology (CAT) is required [2]. To overcome this issue, a model that can quickly analyse and diagnose various brain tumours is needed. One activity that could help the health sector flourish is the automatic diagnostic interpretation of image data. The purpose of this research is to build a model based on machine learning and deep learning that can automatically explore and detect various brain tumours.

The remaining of this paper is organized as follows: Section II presents a literature review, Section III explains Methodology, while experimentations are presented in Section IV, Section V describe results and followed by discussion, while finally conclusions are drawn.

II. LITERATURE REVIEW

According to the World Health Organization (WHO), roughly thirteen thousand people are impacted by the tumor each year. Because of the late diagnosis, the death rate is steadily increasing each year. The largest issue pathologists have in detecting and classifying cancers using manual methods. According to research issued by Cancer.Net and the World Health Organization (WHO), a study in [4] describes an automated architecture for detecting and classifying tumors, which is a new study topic in medicine [5]. This has prompted a number of academics to work on developing a more cost-effective and precise automated method for tumor detection, classification, and diagnosis. A study in [6] demonstrated a deep learning-based segmentation framework based on a 3D CNN architecture. Furthermore, survival prediction using a multimodal MRI scan is discussed. The system employed decision tree-based classification with cross-validation to eliminate model bias and extract 4524 features. The prediction of survival is employed using a random forest approach, which has a 61% accuracy rate for short, mild, and long survivals. Study in [7] employed a fuzzy C means algorithm to detect tumors in MRI pictures of the brain. The tumor region is segmented using morphological segmentation in the observed tumor image. For reliable brain tumour delineation from benchmark medical images, a deep learning model including long short-term memory (LSTM) and convolutional neural networks was suggested in [8]. (ConvNet). Multiple combinations of preprocessing and class weighting models are employed to produce a mixed ensemble of ConvNet and LSTM. This model calculated an 82.29 % Dice similarity score. A paradigm for early tumour detection was proposed in [9]. In this method, the Weiner filter is employed for denoising with probable field clustering. Morphologically segmented FLAIR and T2 MRI images are employed to collect features using fused LBP and GWT. The precision of the proposed model was 93 % and 96 %, respectively. [10] proposed a multi-parameter deep learning model for autonomous meningioma detection and segmentation. This model employed the voxel-wise classification of four tumour classifications defined in the BRATS benchmark. The suggested approach uses preprocessing methods such as bias field correction, registration, and skull stripping. The textural feature improves tumour region prediction accuracy. On the BRATS 2013 and 2015 datasets, this method achieved 92 % accuracy. Using deep learning algorithms, study in [11] presented a network to identify tumor areas in the brain. The detected image is segmented using DWT, and features are extracted using PCA. This non-linear technique yielded a 96.7 % significant simulation result. A study in [12] created a machine learning approach for detecting brain tumour locations and segmenting the affected areas using the energy technique. A random forest classification strategy, which has a 98 % accuracy rate, is also applied. To increase the performance of classification and segmentation, the study in [13] employed reinforcement and enhancement methods. Segmentation is employed based on the temperature mapping of tumor areas in MRI.

Brain tumour MR images of Pituitary, Glioma, Meningioma and Malignant and no tumours are investigated using the proposed model to identify subtle abnormalities. It utilizes both image processing and machine learning-based algorithms. The model is trained to classify the brain MR images on the basis CNN (Alex Net) features and through an ensembled classifier and obtained accuracy of 95.547%.

III. METHODOLOGY

With the advancement of current medical standards, Artificial Intelligence (AI) has become increasingly significant in the field of health care. Various imaging modalities have various features for every tumor. These complications could be detected employing the usual machine learning approach by employing a classifier to separate the MR images into five categories tumours i.e the pituitary, meningioma, malignant, Glioma and no tumour or healthy. The data employed in the proposed experiment was sourced from publicly available databases. ('Brats-2015, Brats-2017 and Brats-2018 Brain tumor MRI Dataset"). images of brain tumors were collected. Each class have 3061 MRI images of tumor's, including meningioma, glioma, pituitary, malignant, and healthy. The next phase was data augmentation; for deep learning, increasing the number of data could enhance training accuracy. According to previous research. The following steps are adapted to develop a machine vision-based technique to automatically detect various brain tumor Shown in Fig. 1. In large datasets, a weak algorithm performs better than a sophisticated algorithm. The augmentation technique was employed to expand the number of images without having to acquire fresh data. To enhance the data in each class, a variety of augmentation approaches were employed (i.e., pituitary, glioma, meningioma, malignant and healthy).

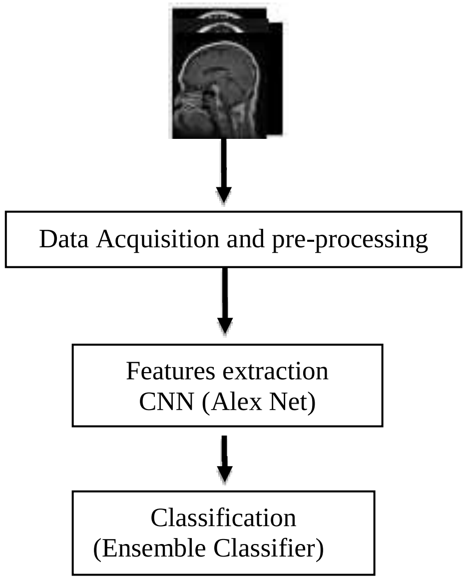

FIGURE 1: Methodology Block diagram

Flipping, rotation, translations, mean filter, median filter, color shifting, and Gaussian filter were employed in this research, resulting in a total of 3061 tumor MR images in each class. After then, all of the images were preprocessed. All images were scaled to 227 by 227 pixels in the first step. Various approaches were employed to enhance the images, including contrast enhancement, noise removal using a de-noising technique, edge sharpening, filtering, histogram equalization, and intensity modification. The region of interest (ROI) for tumor segmentation from MR images was accomplished after image enhancement. Feature extraction is a critical step because each input image has different features. It is important to extract some meaningful features from the input tumor MR images for recognition. To simplify the data and eliminate redundancy, feature extraction was employed. However, a close examination of the tumor MR images reveals that the images exhibit very little contrast in terms of shapes, edges, and textures. As a result, these features would be employed as follows. Initially, Alex Net parameters such as quantization level, displacement direction, displacement magnitudes, and features were optimized to perform a full textural analysis of tumor MR images. To extract features, the image is divided into cells of 3 × 3 pixels each. To diagnose various brain tumours, CNN (Alex Net) analyses quantitative aspects of brain tumours such as shape, texture, and signal intensity.The cell adjacent to it is then compared to it. The centre pixel's values are transformed to 1 and the value of the nearby cells is changed to 0. Finally, each cell's histogram is generated using Equation (1).

$$LBP_{R,T}(T,q) - \sum_{t=0}^{T-1} s(g_t - g_c)\, 2^t, S(t) - \begin{cases} 1 & t > 0 \\ 0 & otherwise \end{cases} \quad (1)$$

The neighbourhood pixels as T-bit binary numbers were differentiated using Equation (1). As a result, binary patterns have distinctive values. The grey level of the local neighbourhood center pixel is mentioned in this equation. It also highlights evenly spaced pixels, where R and S stand for Radius and Sample Images, respectively. A select number of histogram bins is extracted using HOG features. On dissimilar sections of the images, the proposed study uses a greater number of histogram bins. The input images were scaled to 64x128, subsequently, the images were converted to grayscale. Equation (2) were employed to find the gradient for each pixel.

$$\begin{cases} dx = P(x+1, y) - p(x, y) \\ dy = p(x, y+1) - p(x, y) \end{cases} \quad (2)$$

The horizontal and vertical gradients are denoted by dx and dy, respectively, while the pixel value at (x, y) is denoted by p (x, y). An equation was employed to compute the gradient orientation (3).

$$\Theta(x, y) = \tan^{-1}\frac{dy}{dx} \quad (3)$$

IV. EXPERIMENTATION

The Brain tumour MRI image Dataset was gathered from a publicly accessible database and a part of a dataset are collected from hospitals containing images of several forms of brain tumour's, including Pituitary, Meningioma, Glioma, benign, and malignant tumour. To examine and evaluate the images, we provide our novel techniques. The categorization/Classification process was completed as the last stage. The pixels in a digital image were classified into different groups using classification. Ensemble classification is when more than one classifier is combined for prediction purposes in [3]. When compared to an individual model, ensemble improves prediction conformity, resulting in improved accuracy. This method makes use of majority voting, that is, a prediction for each test case is made by each model. The ultimate prediction was chosen based on the number of votes received. In this study, multiple machine learning algorithms for classification were employed based on feature selection. KNN, SVM, Decision Tree, and Random Forest are examples of these. The KNN algorithm locates an unknown data point's nearest neighbour. The value of 'k' affects the algorithm function. The near neighbour is predicted if the value of k equals 'n'. Pituitary, Glioma, Meningioma, Malignant, and No tumour classifications are all present in this research endeavour. A Decision Tree model was created with the goal of calculating the value of various input values for required variables. Numerous decision trees are included in the Random Forest model. In each decision tree, the training data were sampled at random. Subsets of features were then employed to select the dividing nodes. Because it has a greater variance when fitting data, Random Forest overcomes the constraints of the Decision Tree. KNN. The model in SVM plotted each data point in n-dimensional space, where n is the number of features. By integrating multiple features from several various models into one predictive feature, the ensemble classifier aims to improve performance and avoids the danger of employing a single feature retrieved from one model with poor performance. the parameters of proposed ensemble classifier are Decision tree, random forest, KNN, and Support vector Machine (SVM). The goal of classification was to determine the hyper-plane that categorises each class. These algorithms are commonly employed to classify different types of brain tumours utilising tumour MR images in order to get a faster response, and the final decision of Ensemble classifier is based on bagging. A tumour MR image was provided into the system as an input during the experimentation stage. Pre-processing methods were commissioned to eliminate extraneous data from the input image in the next phase. The images were then reduced to 227x227 pixels each. ROI was extracted after pre-processing. Using CNN (Alex Net) algorithms, numerous features from the images were retrieved for subsequent analysis. Statistical features such as mean, mode, median, skewness, and kurtosis were also employed in conjunction with CNN (Alex Net) features. The Pituitary, Meningioma, Glioma, Malignant, and No Tumour classifications were all classified using a multi-class Ensemble Classifier model. 3061 tumour MR images from each class were employed to train the model. The dataset would then be trained to detect and distinguish between several brain tumour types, such as meningioma, glioma, pituitary, malignant, and no tumour, using Ensemble Classifiers. Five fold cross validation is employed in this research

V. RESULTS & DISCUSSION

The proposed model was created to explore and identify microscopic abnormalities in Pituitary, Glioma, Meningioma, Malignant, and no tumour MR images. It involves the utilization of image processing as well as machine learning technologies. The model was trained to recognize CNN (Alex Net) characteristics in brain MR images and classify them. The algorithm modelling for the developed approach was represented in pseudo-code as shown in Table I.

Subsequent to training, the model was tested on unseen data (not involved in training and testing). The results for traditional machine learning classifiers are shown in Fig. 2 (a-e) respectively. Where images from Fig. 2(a) to 2(e) shows the Segmentation for a region of interest. Where Fig. 3(a) represents Malignant tumor, Fig. 3(b) represents Glioma tumor, Fig. 3(c) represents Meningioma Fig. 3(d) represents healthy and Fig. 3(e) represents Pituitary tumor.

TABLE I
PSEUDOCODE FOR THE DEVELOPED METHOD

```
1. for i=input image (Image pre-processing)
if cc ==3
a = rgb2gray(a);
end
2.Feature extraction from each image
Net=alexnet;
3. Train_X (i, :)
4. Test_X (i, :)
for i=1: numel (Test_X (:1))
a= Test_X (i, :);
5. for i=1: numel (Test_X(:1))
a= Test_X (i,:);
all= [predict1 predict2 predict3 predict4];
for i=1: numel (Test_X(:,1))
new_lab2(i,1) = mode(all(i,1:4))
end
```

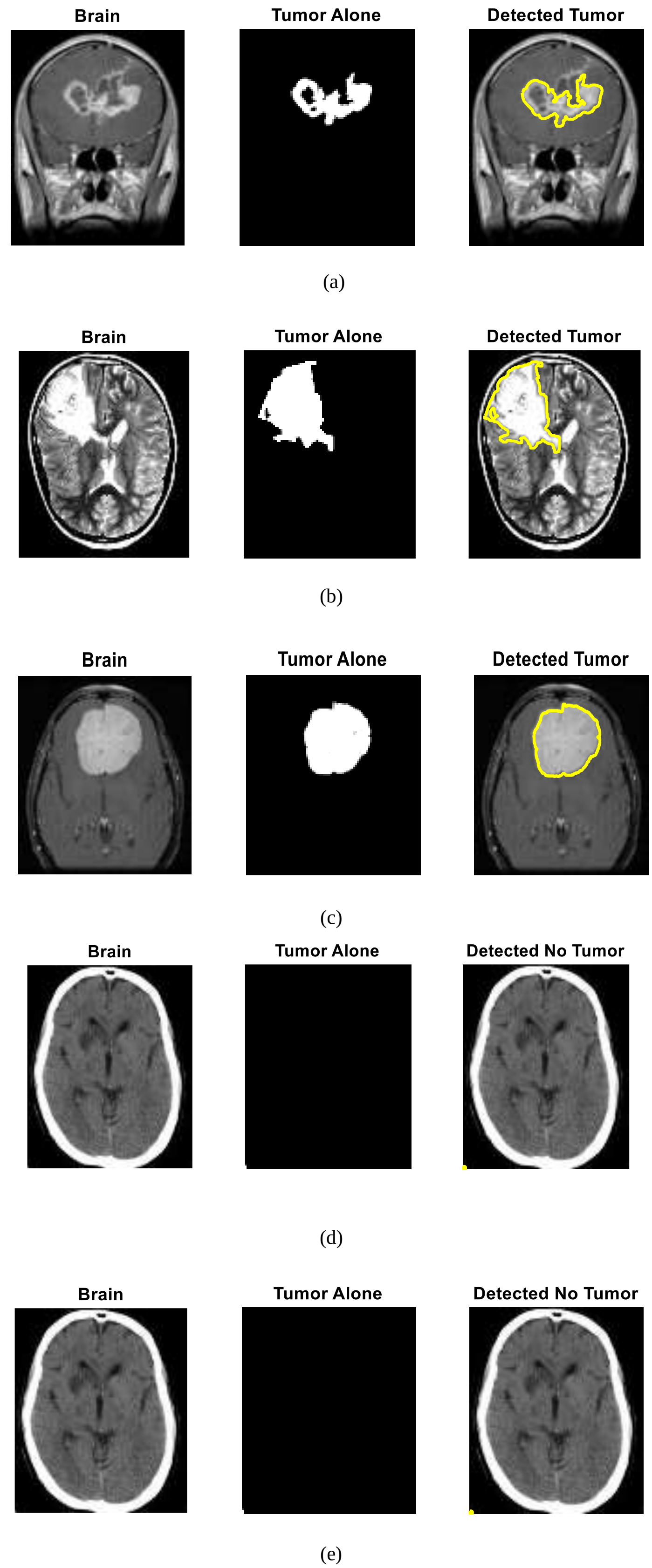

FIGURE 2: Brain Tumor MR Images Segmentation.

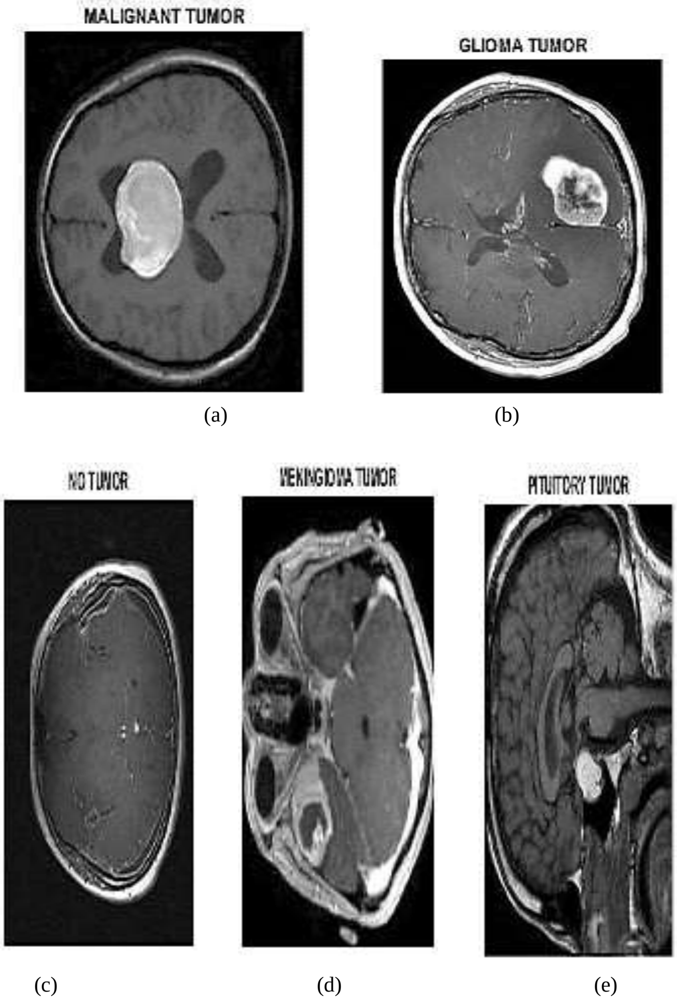

FIGURE 3: Various Tumer

Numerous performance measures were employed to determine the outcomes of the Machine Learning algorithms commissioned in this study. For evaluation purposes, four performance measures were established. The performance of the different methods is compared in Fig. 4 described as detection modules' performance.

These parameters are precision, recall, F1 score, and accuracy as discussed in Table II.

Table II. Performance Statistical test

Classes	***Precision***	***Recall***	***F1 score***	***Accuracy***
Glioma	*0.9706*	0.9377	0.9538	0.954
Malignant	0.9445	0.9459	0.9451	0.954
Meningioma	0.9124	0.9239	0.9180	0.954
Healthy	0.9652	0.9888	0.9768	0.954
Pituitary tumor	0.9929	0.9901	0.9919	0.954

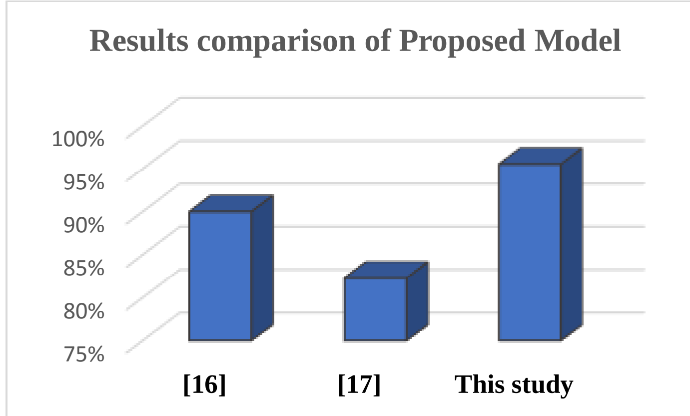

FIGURE 4: A comparison for performance

The method discussed in [16] was limited to detecting benign, Malignant and normal, and [17] was only able to detect tumors. Pituitary, Meningioma, Glioma, Malignant, and healthy tumor were all detected and classified using the developed approach. Table III shows a comparison of the suggested model to some of the developed approaches for a better understanding.

Table III. Comparison table for evaluation

S. No	Reference	Remarks	Methods	Accuracy
1	[16]	Detects Benign, Malignant and normal	KPCA & KSVM	90%
2	[17]	Brain tumor segmentat ion	ConvNet and LSTM	82.29%
4	This study	Meningiom a, glioma, Pituitary, Malignant, healthy	CNN, KNN, SVM, Random Forest, and Decision Tree	95.547%

VI. CONCLUSION

A machine vision-based technique was employed to detect multiclass brain tumor, including meningioma, glioma, pituitary, malignant, and no tumor, in their early stages, that could further rescue precious human lives. The purpose of this research was to develop a model that assists the radiologist in the early detection of the above-mentioned brain tumour in order to avoid fatalities. The proposed model was trained on publicly accessible datasets, and the accuracy, precision, recall, and F1 score of the model were 0.9557, 0.9557, 1.00, and 0.977, respectively. It was determined that the proposed method successfully accomplished the goal of detecting numerous brain tumour that is invisible to the human eye on MR images. At the moment, efforts are being made to incorporate numerous dominant characteristics for better efficiency. Employing knowledge distillation technique for real time brain tumor detection is in progress.

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