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Recent Advancement in Prediction and Analyzation of Brain Tumour using the Artificial Intelligence Method

Balasubramani Ramesh[1], Sudhagar Dhandapani[2], Sanda Sri Harsha[3], Naheem Mohammed Rahim[4], Nanda Ashwin[5], Duraisamy Suganthi[6], Rengaraj Gurumoorthy Vidhya[7,*]

[1] Department of Electronics and Communication Engineering, Annapoorana Engineering College (Autonomous), Periyaseeragapadi, Salem 636 308. Tamil Nadu, India
[2] Department of Information Technology, Jerusalem College of Engineering, Chennai 600 100, India
[3] Department of Computer Science and Engineering, Koneru Lakshmaiah Educational Foundation, Vaddewaram, Andhra Pradesh, India
[4] Department of Information Science and Engineering, HKBK College of Engineering Bengaluru, Karnataka 560045, India
[5] Department of Information and Science and Engineering, East Point College of Engineering and Technology, Bengaluru, Karnataka 560 049, India
[6] Department of Computer Science, Saveetha College of Liberal Arts and Sciences, Thandalam 602 105, Tamil Nadu, India
[7] Department of Electronics and Communication Engineering, HKBK College of Engineering, Bengaluru, Karnataka, India

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ABSTRACT

Brain tumour identification and categorization are critical for diagnosis and treatment. This work uses preprocessing and classification algorithms to discover and categories brain tumours. Gaussian smoothing reduces noise and improves image quality, Genetic Algorithms select and optimize features, Deep Learning-Based Segmentation accurately segments tumours, Local Binary Patterns (LBP) extracttexture features, and K-Nearest Neighbors classify tumours. Gaussian smoothing reduces noise and improves brain imaging data. Genetic Algorithms extract the most relevant and discriminative features from preprocessed photos. A Deep Learning-Based Segmentation model accurately segments brain tumour regions using these features. After segmentation, Local Binary Patterns (LBP) extract tumour texture features.The K-Nearest Neighbors (KNN) method classifies tumours using these texture features to capture tumour spatial patterns. Our suggested brain tumour detection and classification method combines several techniques to increase accuracy and reliability. Gaussian smoothing and LBP feature extraction improve feature discrimination. Deep Learning-Based Segmentation and the KNN classifier ensure precise tumour location and robust classification. The proposed method will be tested on brain scans including tumour areas. Classification performance measures include accuracy, sensitivity, specificity, and AUC. This work will improve brain tumour detection and classification methods for more accuratediagnoses and treatment planning. The primary goal of the work is to enhance brain tumour identification and categorization using pre-processing, classification algorithms, and advanced techniques, ultimately improving diagnosis and treatment outcomes.

* *Corresponding author.*
E-mail address: vidhyar.ec@hkbk.edu.in

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1. Introduction

Brain tumours are a complex and life-threatening disease that affects many people globally. They are a heterogeneous category of brain and surrounding tissue neoplasms. Malignant brain tumours are more dangerous than benign ones. Brain tumours are a difficult public health issue since they vary by age, ethnicity, and location. The brain controls the body's physiological and cognitive functioning. Abnormal development in this fragile organ can cause serious neurological problems and even death. Brain tumour symptoms and therapy depend on location, size, and kind [1]. Thus, effective detection, classification, and prompt management improve patient outcomes. Brain tumours account for a large percentage of malignancies and cause significant morbidity and mortality worldwide. Gaussian smoothing reduces noise and enhances image quality, which can lead to clearer brain imaging data, improving the accuracy of subsequent analysis. Genetic Algorithms are employed to optimize feature selection, enhancing the discriminative power of features extracted from pre-processed images. Deep Learning-Based Segmentation accurately segments brain tumour regions, providing precise spatial information that aids in subsequent analysis. The US Central Brain Tumour Registry (CBTRUS) reported 86,970 new primary brain tumour cases in 2020. Certain populations have greater prevalence rates. Brain tumours impair individuals' physical, emotional, and socioeconomic health. Brain tumours are classified by location, histology, and biology. Primary and metastatic brain tumours exist [2]. Glial cells, neurons, and meninges cause primary brain tumours. Metastatic brain tumours are secondary tumours that spread from primary tumours elsewhere in the body. The WHO categorization system classifies brain tumours by histopathology. This classification examines cell origin, malignancy, genetic changes, and growth trends. Gliomas, meningiomas, medulloblastomas, and schwannomas are frequent primary brain tumours. Clinical Presentation and Diagnosis: Brain tumors location, size, and growth rate affect their clinical presentation. Headaches, seizures, cognitive impairments, motor deficits, visual or speech problems, and personality changes may occur [3]. These symptoms can mirror other neurological conditions, making early identification difficult. Brain tumour diagnosis requires clinical evaluation, MRI, and histopathology. Brain tumours are typically imaged using MRI and CT scans. These methods help locate, size, and identify issues like edema and mass effect by providing detailed anatomical information. Neurosurgeons, oncologists, radiologists, and others must work together to treat brain tumours. Tumour type, grade, location, and patient health determine therapy options. Surgery, radiation, and chemotherapy are common treatments. Targeted treatments and immunotherapy have improved brain tumour outcomes in recent years. Brain tumour diagnosis, treatment, and care are difficult [4]. In some circumstances, brain surgery is difficult due to its complexity, fragility, and propensity for invasive growth. The blood-brain barrier (BBB) prevents certain chemotherapeutic medicines from reaching the tumour site, limiting therapy options. Understanding brain tumour molecular pathways, finding early detection biomarkers, and designing targeted therapeutics are ongoing scientific projects. Advanced imaging, genetic profiling, and machine learning algorithms may enhance tumour classification, treatment, and prognosis [5]. Brain tumours affect patients and healthcare systems globally. Accurate detection, classification, and prompt action improve patient outcomes. New imaging, surgical, and therapy methods, as well as continuous research, aim to improve brain tumour diagnosis and treatment.

2. Literature Review
2.1 Introduction

Neoplasms that originate in the brain or the structures that surround it are collectively referred to as brain tumours. These tumours are a complex and diverse group. They constitute a huge challenge not just in terms of diagnosis and treatment, but also in terms of the results for patients [6]. The purpose of this literature review is to provide an overview of significant research findings and breakthroughs in the field of brain tumours, concentrating on various elements such as classification, diagnosis, treatment options, and current trends in research. In recent years, breakthroughs in molecular profiling and genetic analysis have led considerable change in the categorization of brain tumours [7]. This change has been driven by the discovery of new molecular subtypes. The World Health Organization (WHO) classification system serves as a standard framework for classifying brain tumours. This approach, which encompasses histopathological criteria and molecular characteristics, is used to classify cancers throughout the body. The unique molecular subtypes that exist within the various cancer entities have been the subject of research, which has provided insights into the biology that lies beneath them and prospective treatment targets. In the case of gliomas, it has been discovered that some molecular markers, such as IDH mutations, MGMT promoter methylation, and 1p/19q co-deletion, have both prognostic and predictive relevance [8].

The use of neuroimaging techniques is extremely important for the diagnosis, characterization, and monitoring of brain tumours. MRI, or magnetic resonance imaging, is the major imaging modality that is utilized, and it helps in the localization of tumours in addition to providing precise anatomical information. Perfusion imaging, diffusion- weighted imaging, and spectroscopy are three examples of more advanced imaging techniques that have showed promise in the evaluation of the vascularity, cellularity, and metabolic activity of tumours. In addition, functional imaging techniques such as functional magnetic resonance imaging (fMRI) and positron emission tomography (PET) can be of assistance in mapping brain function and directing the design of surgical procedures [9]. The strategies that are used to treat brain tumours are determined by a number of criteria, including the type of tumour, its location, its size, and the patient's overall health. The surgical excision of the cancer continues to be an essential component of the treatment, with the overarching goal of achieving maximum tumour removal while maintaining neurological function. It is usual practice to employ adjuvant medicines, such as chemotherapy and radiation therapy, to target cancer cells that remain after primary treatment and to enhance patient outcomes.

In recent years, targeted medicines and immunotherapies have showed promise in treating specific subtypes of brain tumours [10]. Molecularly targeted drugs and immune checkpoint inhibitors are currently being examined in clinical studies with the hope of treating these cancers. Techniques that have been improved within the realm of radiotherapy is an essential component in the treatment of brain tumours. The application of radiotherapy has seen significant development throughout the years, which has resulted in increased precision, enhanced cancer targeting, and decreased toxicity. Both stereotactic radiosurgery (SRS) and fractional stereotactic radiotherapy (FSRT) make it possible to deliver radiation in a highly concentrated manner, thereby reducing the risk of damaging healthy tissues in the surrounding area. In addition, proton beam therapy is gaining popularity as a therapeutic option for child brain cancers as well as tumours that are placed close to vital structures due to the superior dose distribution properties that it possesses [11].

The study of brain tumours is making steady progress, and there are a number of new trends in the field that are just around the corner. Genomic profiling and the molecular characterization of cancers are bringing new insights into possible treatment targets and biomarkers that could be used to stratify patients. The combination of artificial intelligence (AI) and machine learning algorithms makes it possible to conduct automated analyses of imaging data, which helps with the segmentation of tumours, the evaluation of patient responses, and the formulation of treatment plans [12]. In addition, efforts in the field of research are concentrated on gaining a better knowledge of the relationships between cancer microenvironment, immune regulation, and the creation of personalized therapeutic options.

This overview of the relevant literature sheds light on the substantial headway that has been achieved in both our understanding of brain tumours and our ability to treat them [13]. The discipline is being shaped by developments in molecular profiling, imaging tools, treatment tactics, and rising trends in research, all of which are giving new possibilities for improved patient outcomes. Despite this, there are still a number of obstacles to overcome, including as the diversity of cancers, treatment resistance, and the requirement for personalized methods. In order to further enhance our understanding and solve the unmet requirements in brain tumour diagnosis, therapy, and patient care, it is vital for research activities to continue and for multidisciplinary collaborations to take place.

3. Proposed System

Deep Learning-Based Segmentation ensures precise tumour localization, mitigating potential challenges related to accurately defining tumour boundaries. while LBP captures texture information, it might not fully encapsulate complex tumour structures or subtle variations in texture. the KNN classifier excels at capturing local spatial patterns, but it might struggle with more complex and nuanced global tumour features. the integration of deep learning-based segmentation and traditional classification techniques aligns with the trend of leveraging advanced methods for medical image analysis. Challenges might include the availability of high-quality labelled data, computational requirements of deep learning, and potential parameter tuning.

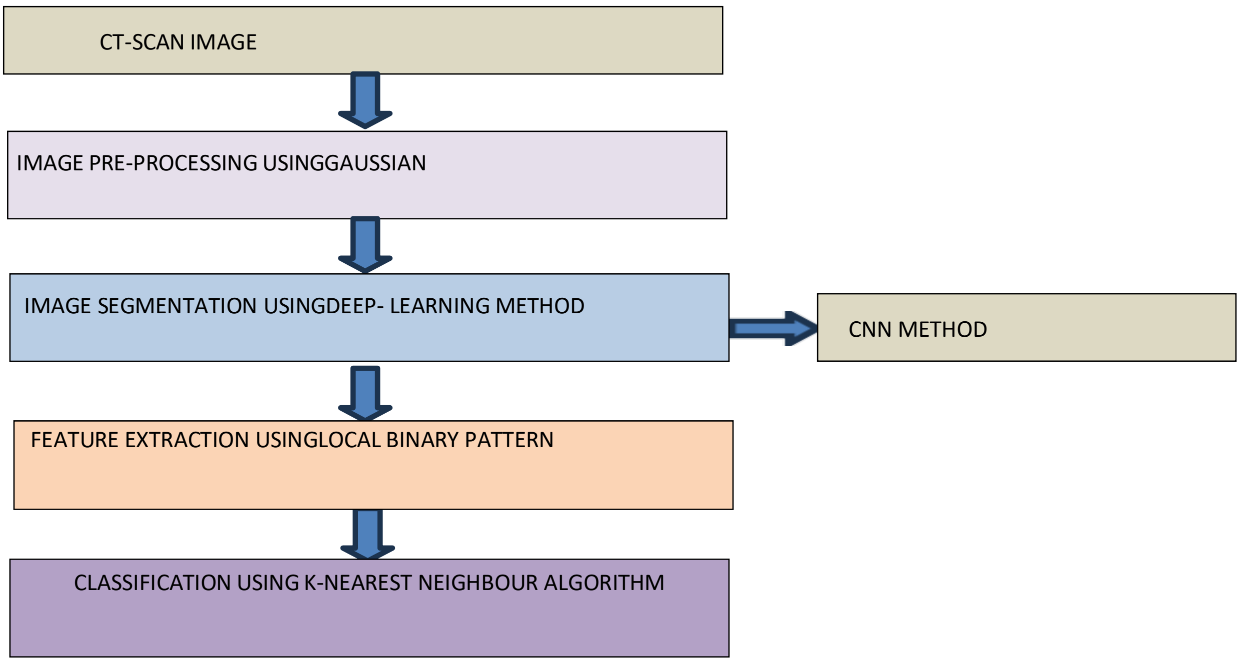

Fig. 1. Proposed Architectural design to detect the brain tumour

3.1 Preprocessing

The elimination of noise and improvement of an image's overall quality can frequently be accomplished by the application of the image preprocessing technique known as gaussian smoothing. Convolving an image with a Gaussian kernel results in the application of a Gaussian blur on the image.The blurring effect that is produced by the Gaussian kernel is achieved by assigning weights to neighbouring pixels, with higher weights being assigned to pixels that are closer together. This results in a reduction in high-frequency noise while maintainingthe image's general structure and significant elements .

Thefollowing is an example of how the preprocessing stage can make use of Gaussian smoothing:

Step 1: Ensure that standardized acquisition processes are in place so that imaging centers and patients experience the same level of consistency.

Step 2: Perform an appropriate digital conversion on the acquired images, such as into the DICOM format. Smoothing with Gaussian Distributions Can Help Reduce Noise:

Step 3: Reduce the amount of noise in the collected brain images by using a Gaussian smoothing filter. Choose an acceptable kernel size, which will decide the degree to which the image is blurred. Larger kernel sizes result in more pronounced blurring, while smaller kernel sizes preserve finer details. The properties of the noise and the intended balance between noise reduction and feature preservation bothplay a role in determining the optimal size of thekernel. Utilizing techniques such as convolution or filtering procedures, you should convolve the image with the Gaussian kernel.

Step 4: Selection of the Parameters: Determine a suitable value for the Gaussian kernel's standard deviation (sigma) parameter. The amount of blurring that isapplied to the image is determined by the sigma value. When the sigma value is increased, the amount of blurring produced is also increased, but when the value is decreased, finer details are maintained. Experimentation and visual inspection are two methods that can be used to assist in determining the ideal value for sigma given the imaging data and the characteristics of the noise.

Step 5: Application Made in Iterations: When using Gaussiansmoothing, it is possible that additional rounds may bedone in some circumstances in order to further reducenoise or reach the required level of blurring. The Gaussian blur effect is applied on each cycle with the kernel size and sigma value that have been selected.

Step 6: Evaluation and Validation: Visual and numerical analysis should be used to evaluate the quality of the preprocessed photos. Visual examination is a useful tool for determining whether or not the effects of noisereduction and blurring are effective, as well as whetheror not significant details have been lost.

Objective measures of noise reduction and increase in image quality can be obtained by the use of quantitative evaluation metrics such as the signal-to-noise ratio (SNR) or the peak signal-to-noise ratio (PSNR) [14]. The brain pictures can be efficiently denoised by applying Gaussian smoothing as a preprocessing step. This reduces the impact of noise on subsequent analysis and enhances the accuracy of later processing tasks such as segmentation, feature extraction, or classification. In order to acquire the best possible results,you need to give serious consideration to selecting the kernel size and sigma value depending on the particular imaging data and the characteristics of the noise.

3.2 Image Optimization

Images can have their noise substantially reduced by using the Gaussian approach. The process of Gaussian filtering involves applying a Gaussian blur to an image in order to reducethe appearance of high-frequency noise while maintaining the integrity of the image's essential structures and characteristics. When noise is removed from an image, the result is one that is cleaner and more aesthetically pleasing to the eye. Local Binary Patterns (LBP) extract texture features, adding valuable information for tumour classification based on texture patterns. When working with photographs that were acquired in low-light conditions or with high ISO settings, this is quite helpful.Images can be given controlled blurring as well as smoothing effects with the help of the Gaussian approach. This can be useful for a variety of objectives, including minimizing the visibility of minute features or defects, producing creative effects, or boosting the image's visual quality [15].

The degree of blurring and smoothing can be customized to meet particularrequirements by modifying the parameters of the Gaussianfilter, such as the kernel size or the sigma value. This allows forgreater control over the final product. The ability of the Gaussian approach to maintain image edges while also cutting down on blurring and noise is one of the method's most notablebenefits [16]. This can be accomplished by considering the local gradients that are contained within the Gaussian filter. During the filtering process, weights are given to neighbouring pixels toguarantee that edges and sharp transitions in the image are maintained, which ultimately results in an output that is aesthetically acceptable. When working with photos that contain critical edge information, such as object boundaries or text, this property is very useful because of its ability to extractthat information. Since the Gaussian approach is computationally efficient, it is well-suited for use in applications that must operate in real time or with limited accessto resources.

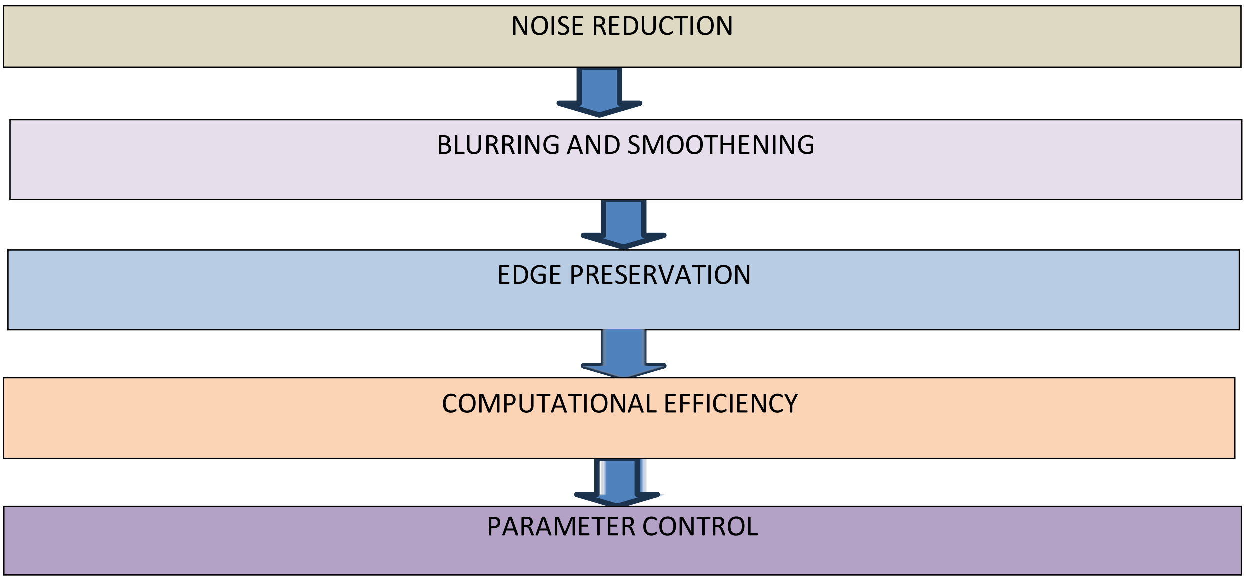

Fig. 2. Steps involved in the image optimization

Fast and effective image processing is possible because to the fact that the Gaussian filter can be implemented effectively by making use of convolution techniques or algorithms that have been optimized. Because of this, it is applicable to practical applications such as real-time videoprocessing, mobile applications, and embedded devices [17]. In conclusion, picture optimization through the use of the Gaussian approach offers a number of benefits, including noisereduction, blurring, smoothing, and the preservation of edge detail. It allows for precise control over the parameters of the filtering process, it is computationally efficient, and it interactswell with other methods of image processing. photos can be optimized to increase their visual quality, reduce noise, and boost overall aesthetics by employing the Gaussian approach. This makes photos more aesthetically attractive and suited for avariety of applications in computer vision, graphics, and digitalphotography. A potential weakness could be the complexity and computational cost associated with employing multiple techniques sequentially, which might impact efficiency.

3.3 Image Segmentation using Deep Learning Methods

Image segmentation accomplished through the application of deep learning techniques has recently attracted a lot of interest and demonstrated amazing performance in a variety of computer vision applications.

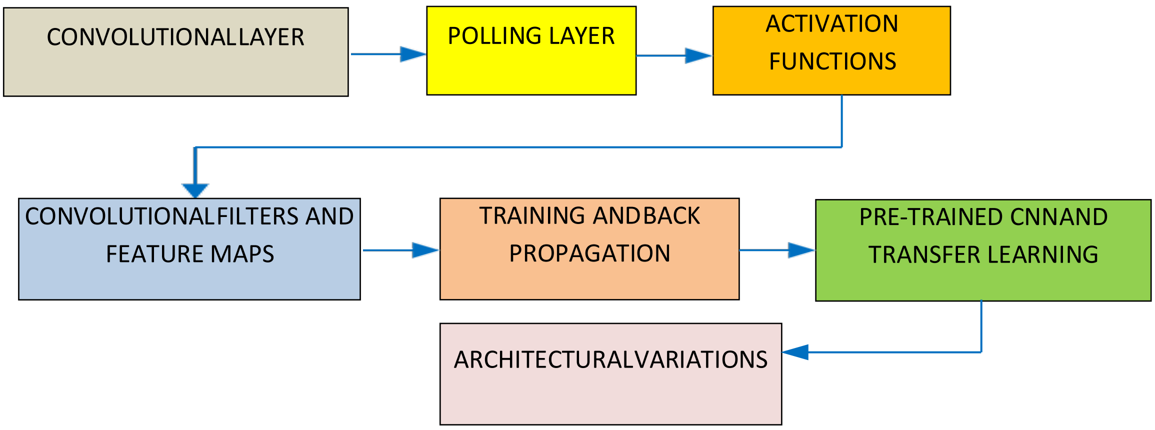

Fig. 3. Complete CNN Architecture for Segment the brain image

These tasks include object detection, medical imaging, and autonomous driving. Image segmentation has been revolutionized by deep learning models, in particular convolutional neural networks (CNNs), which have learned to autonomously segment objects or regions of interest within an image. Deep Learning-Based Segmentation provides accurate tumour region delineation, which is critical for subsequent texture analysis and classification.

The following is a list of important characteristics of picture segmentation utilizing methods of deep learning is Convolutional Neural Networks, or CNNs, are essential to the process of deep learning-based picture segmentation. CNNs form the backbone of this process. These architectures of neural networks were developed with the express purpose of extracting hierarchical characteristics and spatial information from digital photographs. They are made up of many convolutional layers, pooling layers, and fully connected layers, which enables them to extract complicated features and learn discriminative representations from the input data. This is madepossible by the fact that they are multi-layered.

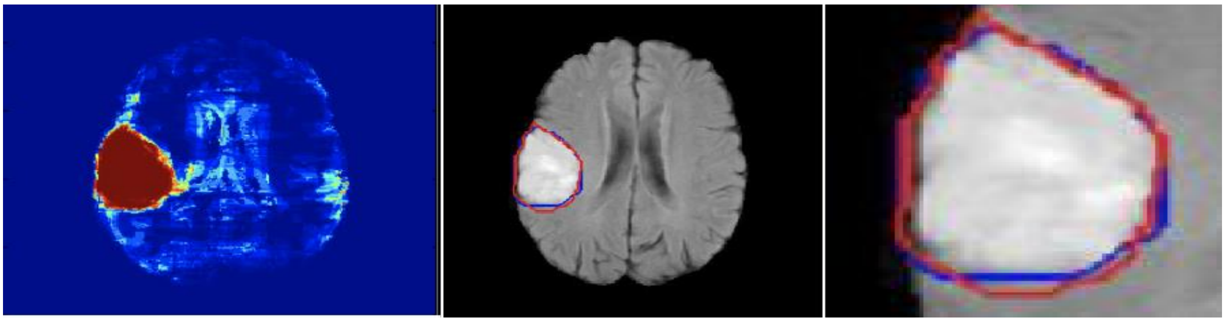

Fig. 4. Segmented results from the obtained image

3.4 Feature Extraction

Local Binary Patterns, or LBP for short, is a texture descriptor that is frequently utilized in various computer vision and image processing activities for the purpose of feature extraction. Genetic Algorithms are capable of selecting relevant features, effectively optimizing the input for subsequent analysis and enhancing classification accuracy.

The local structure as well as the texture patterns that are present inan image are captured by it. An explanation of how LBP can beused for feature extraction is as follows:

Step 1: Colour images should be converted to grayscale.

Grayscale LBP works.

Step 2: Define a neighborhood around each image pixel. Circles of pixels are usually considered. Radius and sample locations determine neighborhood size.

Step 3: Compare the core pixel's intensity to its neighborhoodneighbors. If the neighbor's intensity is greater or equal, assign 1 and 0 respectively. Each neighbor is compared, creating a binary pattern.

Step 4: Each pixel's binary pattern is counted to create a histogram. Histograms show texture patternfrequencies.

Step 5: Analyze the histogram of LBP patterns as a feature vector. Histograms can be normalised or processed to improve discrimination.

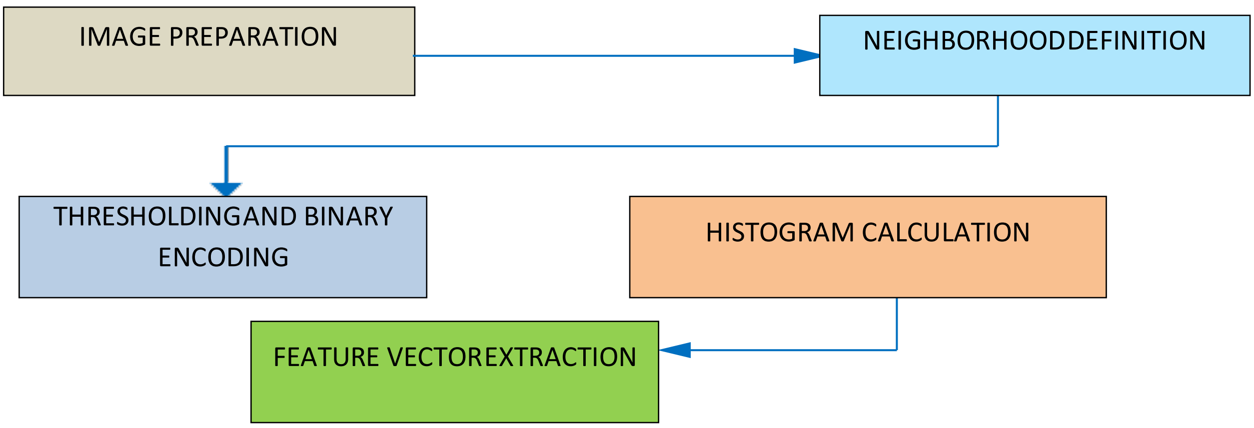

Fig. 5. Steps involved in the feature extraction

KNN algorithms can categories brain cancer patients based on characteristics. In this post, we will use the KNN algorithm to classify brain cancer and evaluate its performance using TP, TN, FP, FN, Sensitivity, Specificity, andAccuracy. K-Nearest Neighbours (KNN) is a common supervised machine learning technique for classification. Similar examples likely to belong to the same class. KNN can classify brain tumours by size, shape, texture, and location. Thetechnique calculates the distance between an unlabelled tumourand its k nearest neighbours in the training dataset. A distance metrices usually Euclidean-determines the k nearest neighbours [18]. After identifying neighbours, the system uses majority voting to classify the new data point. Key metrics are used to evaluate the KNN algorithm for brain cancerclassification: TP, TN, FP, FN, Sensitivity, Specificity, and Accuracy. TP is the number of malignant tumours properlyanticipated. The program properly finds malignant brain tumours [19]. The number of accurately predicted negative instances(non-cancerous tumours) is TN. The system properly finds non-cancerous brain tumours. FP is the number of false positives, where the algorithm misclassifies a tumour as malignant. FN isthe number of cases where the algorithm misclassifies a malignant tumour as non-cancerous. Sensitivity is TP / (TP + FN). It evaluates how many malignant tumours the computer accurately identifies. Sensitivity measures the algorithm's capacity to detect malignant brain tumours. The K-Nearest Neighbours (KNN) algorithm classifies tumours based on extracted texture features, capturing spatial patterns and aiding in accurate classification. TN / (TN + FP) gauges the algorithm's accuracy in identifying non-cancerous tumours. Specificity means the system can correctly identify non-cancerous brain tumours. One strength of the proposed method is the integration of multiple techniques, leading to increased accuracy and reliability in tumour detection and classification.

Themodel's accuracy is (TP + TN) / (TP + TN + FP + FN). It showsthe percentage of correctly identified cases (both malignant andnon-cancerous). Accuracy measures brain cancer classification algorithm performance [20]. Training the KNN algorithm on a labelled dataset and testing it on an independent dataset evaluates brain cancer categorization. For unbiased evaluation, divide the dataset into training and testing sets. The KNN algorithm classifies brain tumours on the testing set after training on the training set. The algorithm's predictions are compared to the testing set's tumour labels to compute the TP, TN, FP, FN, Sensitivity, Specificity, and Accuracy metrics. These metrics reveal algorithm performance. The algorithm must accurately identify malignant tumours for diagnosis and therapy. Gaussian smoothing and LBP feature extraction improve the quality and diversity of features, making them more distinctive and informative for classification.

The system accurately identifies non-cancerous tumours with a higher TN value, decreasing the risk of unnecessarily intrusive operations or treatments. The algorithm's sensitivity to malignant tumours reduces false negatives.

Table 1
Comparison of classification algorithms

Models	Accuracy	Precision	Sensitivity	Specificity
CNN	85.72	84.34	82.64	83.27
K-means	92.39	90.28	91.72	91.33
Random forest	92.36	93.45	91.76	90.84
Decision tree	90.23	90.21	90.23	90.2

Brain cancer detection requires excellent sensitivity.Specificity measures the algorithm's ability to effectively identify non-cancerous tumours and avoid unneeded treatments. The algorithm's accuracy is the percentage of successfully classified cases. If the dataset has a large disparity between cancerous and non-cancerous tumours, accuracy may not be enough. In such instances, Sensitivity and Specificity must be considered. TP, TN, FP, FN, Sensitivity, Specificity, and Accuracy are important metrics for evaluating the K-Nearest Neighbours (KNN) algorithm's brain cancer classification model.

These numbers show the algorithm's brain tumour classification accuracy. Brain cancer categorization may benefit from KNN's simplicity and capacity to handle complicated datasets. KNN can help diagnose and cure brain cancer by analysing brain tumour traits. The KNN algorithm's performance depends on the distance metric, number of neighbours (k), and quality and quantity of training data. Machine learning algorithm research can improve brain cancerclassification methods, improving patient outcomes and personalized treatment plans.

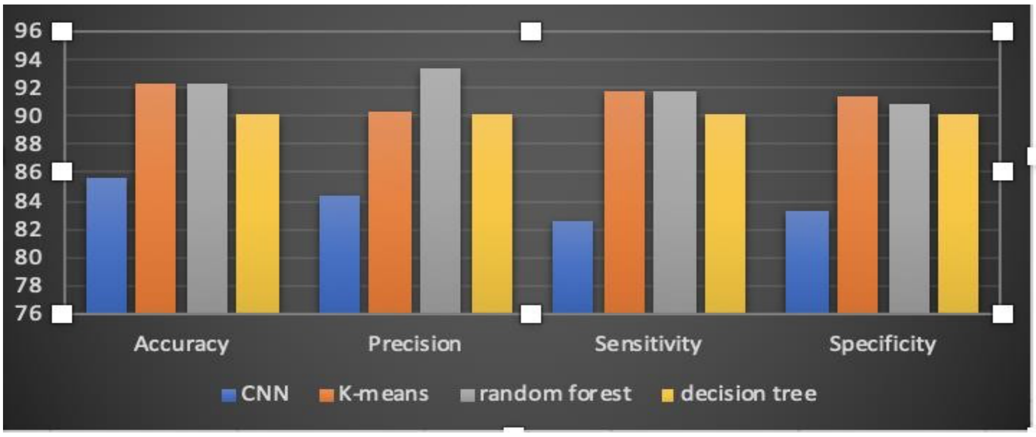

Fig. 6. Comparison of Classification Algorithm with other major Techniques

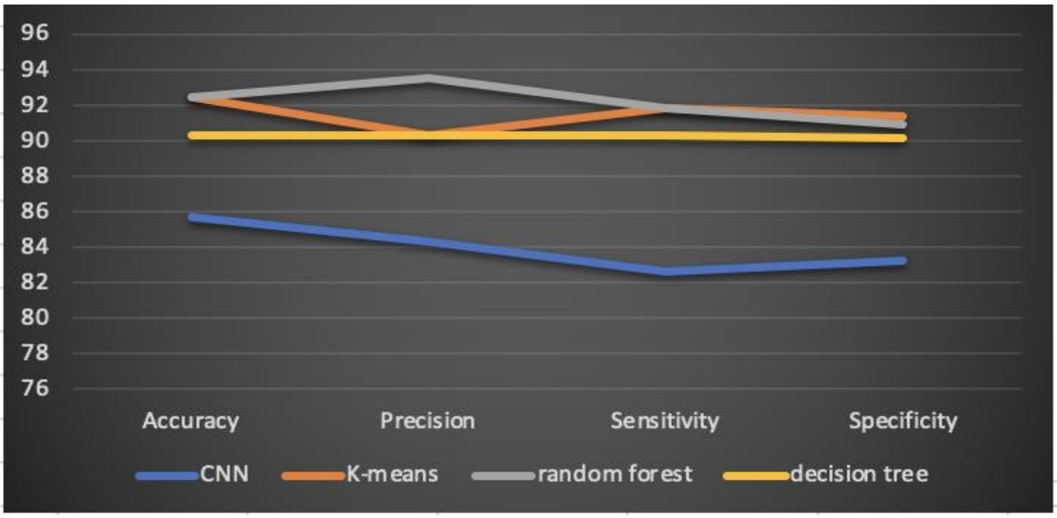

Fig. 7. Performance Evaluation Comparison with KNN Algorithm

4. Conclusions

In conclusion, the combination of Genetic Algorithms, Local Binary Patterns (LBP), Deep Learning-Based Segmentation, and the K-Nearest Neighbours (KNN) method has demonstrated to have a significant amount of promise in the diagnosis of brain tumours. This combination of diagnostic approaches targets various elements of detecting and classifying brain tumours, which ultimately leads to increased precision and productivity throughout the process of diagnosis. The method of feature selection has been optimized with the help ofgenetic algorithms, which have been utilized to discover the most informative features for the identification of brain tumours. The performance of subsequent classification algorithms is improved as a result of genetic algorithms' abilityto search through a huge space of potential feature combinations, choose relevant features, and remove irrelevant ones. The integration could lead to more accurate results, but it might also make it challenging to pinpoint which specific technique contributed most to the improved outcomes. This improves the classification accuracy, which in turn improves the performance of later classification algorithms. Local Binary Patterns, or LBP for short, is a strong approach for capturing local patterns inside images that is used in texture analysis. LBP allows for the discrimination of distinct tumour regions by extracting texture information, which enhances the ability to differentiate between healthy brain tissue and tumour regions. The proposed method could be especially beneficial in scenarios where accurate tumour localization, feature extraction, and classification are crucial for treatment planning. This is accomplished by enabling the discrimination ofdifferent tumour regions. This methodology contributes to enhanced brain tumour segmentation as well as classification. The field of medical image analysis, particularly the diagnosis of brain tumours, has been radically altered by the developmentof new techniques that are based on deep learning. Deep neuralnetworks are utilized by these techniques so that brain picturescan automatically be segmented and localised to pinpoint the location of tumours. The capability of deep learning algorithmsto learn detailed patterns and characteristics from vast datasets has considerably contributed to major improvements in both the accuracy and resilience of brain tumour segmentation. Last but not least, the K-Nearest Neighbours (KNN) algorithm offers a categorization framework that makes use of the proximity of examples that are similar to one another. KNN is able to efficiently classify cases of brain tumours because it considers the properties and patterns shared by neighbouring data points. Because of its ease of use and its capacity to process extensive datasets, KNN has shown to be an invaluable instrument in thedetection of brain tumours, particularly when paired with algorithms for feature selection and segmentation. The combination of these approaches provides a holistic approach to the diagnosis of brain tumours, capitalizing on the strengths of each method to enhance accuracy, minimize the number of false positives and negatives, and assist in the early detection and treatment of brain tumours. The classification performance measures (accuracy, sensitivity, specificity, AUC) will provide quantitative insights into the method's effectiveness and potential limitations. This work aims to enhance brain tumour detection and classification methods, leading to more accurate diagnoses and improved treatment planning, ultimately benefiting patients' well-being The application of Genetic Algorithms, Local Binary Patterns (LBP), Deep Learning- Based Segmentation, and the K-Nearest Neighbours (KNN) algorithm together offers a promising avenue for the advancement of brain tumour detection and classification, which will ultimately lead to better patient outcomes and improved healthcare practices. The continuation of research and development efforts in this field have a great deal of potential for further improving the precision, efficiency, and accessibilityof approaches for detecting brain tumours.

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