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Brain Tumor Grade Detection using Multi Level Weighted Group Feature Set Based Dissimilar Region Detection using Machine Learning Technique

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Abstract: Brain tumours are disreputably dangerous and difficult to treat. Brain tumours are identified by a laborious and error-prone process of manual visual inspection of pictures and manual marking of the suspicious areas by medical specialists. Magnetic Resonance (MR) images have had their ambiguity resolved in a more straightforward fashion. The work analyses the MRI images considered from public dataset providers. In recent years, researchers have proposed automating ways to detect brain cancers at an early stage. The tumour is a common malignant development with atypical features. Tumors of the brain are a form of abnormal growth of tissue in which cells multiply rapidly and out of control. Nature, origin, development rate, and maturity level are used to define its many varieties. Traditional methods of tumour detection are laborious, limited in their ability to effectively process vast amounts of data, and inaccurate. Hence, computer-aided diagnosis relies heavily on MRI's ability to automatically detect brain cancers. Variations in tumour location, shape, and size present a significant obstacle for brain tumour detection. The importance of early detection of brain cancers cannot be overstated. Methods based on computational intelligence can aid in the diagnosis and categorization of brain tumours with accurate grade detection that helps in proper treatment. To aid doctors in the early detection of malignancies with accurate grade detection, a Multi Level Weighted Group Feature Set based Dissimilar Region Detection (WGFS-DRD) for accurate grade detection in brain tumor detection. The proposed model is compared with the traditional models and the results represents that the proposed model performance is high.

Keywords: *Brain Tumor, Tumor Grade, Magnetic Resonance Imaging, Feature Extraction, Weight Allocation, Dissimilar Region Detection.*

1. Introduction

Malignant and benign neoplasms are the medical terminology for tumours, and there are over two hundred different types that can afflict people. The American Cancer Society describes brain tumours as a devastating disease that causes significant impairment of brain function due to the abnormal growth of brain tissue [1]. According to the National Brain Tumor Foundation (NBTF), deaths caused by brain tumours have grown by 300 percent over the past three decades. If not treated, a brain tumour can be fatal [2]. Brain tumours are notoriously difficult to diagnose and treat due to their unique characteristics. The survival percentage of patients with brain tumours is significantly impacted by early diagnosis and treatment [3]. Unlike other types of biopsies, those done on brain tumours require surgical intervention [4]. Consequently, it is essential to find an alternative way for precise diagnosis that does not involve surgery. The most accurate and widely used method for diagnosing brain cancers is MRI [5].

The use of MRI is prevalent in the diagnosis of brain malignancies. It provides a sensitive contrast between tissues and is a popular non-invasive imaging design [6]. Because MRI can image normalized tissue, it can be useful for examining structures of interest in human brain tumours. Manually segmenting brain MRI images is a challenging problem that researchers have recently encountered [7]. It is crucial to have a reliable approach for categorizing brain tumours and their sites. Segmentation and volume estimation of medical images are vital aids in radiation oncology and other medical fields [8]. Knowing where a tumour is located in the brain might help pinpoint the specific causes of a patient's symptoms. Recently developed machine learning techniques have allowed for the recognition and categorization of diagnostic imaging patterns. One of the areas where progress has been made is in the ability to learn not from experts or scientific texts, but rather from data [9]. Medical professionals are increasingly turning to machine learning to aid in a wide range of tasks, from prognosis and diagnosis to molecular

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and cellular structure identification to tissue segmentation and image categorization [10]. The MRI image tumor and tumor size detection is shown in Figure 1.

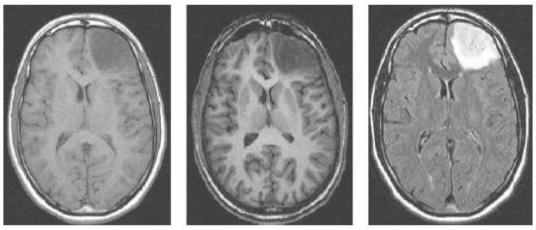

Fig 1: Tumor Detection in MRI

With feature extraction, the effort needed to adequately explain a large dataset is reduced. The complexity of the data being analyzed is exacerbated by the large number of variables involved [11]. Massive amounts of memory and processing power are required, otherwise the classification algorithm relies heavily on the training sample and performs badly on subsequent examples. The process of building variable combinations in order to address these problems and provide sufficient explanations of the data is known as feature extraction [12]. In order to aid in the robust, accurate classification and segmentation of objects, texture analysis seeks to recognize a specific manner to convey the essential feature of textures and represent them in some simpler but unique form [13]. Texture is important for image analysis and pattern identification, but only a few architectures provide on-board textural feature extraction. In any application that involves image processing or analysis, feature extraction and selection are crucial steps that must be taken in order to achieve the desired results [14].

Discrimination, optimality, dependability, and independence are the primary factors to examine while selecting significant features for feature extraction and selection, with the goal of maximizing the features' differentiating performance capacity on the relevant database [15]. Using too many features increases the classifier complexity and diminishes the system performance, while using too few features increases miss-classification results. This is especially true for classification methods like the support vector machine and artificial neural networks, where the dimension of subspace not only affects on their performance but also determines the algorithm training time [16]. Brain tumours can be classified as either slow-growing or aggressive. Tumors can be classified as benign or malignant based on whether or not they spread to other tissues. Brain tumours are graded from I to IV by the World Health Organization [17]. Tumors of grade I progress slowly and seldom metastasize. They are connected with improved survival rates over the long run and can be virtually entirely eliminated surgically. Grade 1 pilocyticastrocytoma is an example of a benign brain tumour [18]. The growth rate of grade II tumours is similar to that of grade I cancers, however grade II tumours can metastasize to other organs. These tumours can even return after surgery has been performed [19]. One such tumour is oligodendroglioma. Tumors of grade III progress more rapidly than those of grade II and may spread to adjacent tissues [20]. Surgical removal of these tumours is usually followed by radiation or chemotherapy [21]. Anaplastic astrocytoma is a kind of tumour that fits this description. Grade IV tumours are the most dangerous because they can spread quickly and to other parts of the body [22]. They could even exploit vascular systems to expand rapidly. This category includes tumours like glioblastoma multiforme [23]. To aid doctors in the early detection of malignancies with accurate grade detection, a Multi Level Weighted Group Feature Set based Dissimilar Region Detection for accurate grade detection in brain tumor detection.

2. Literature Survey

Classifying Brain Tumors (BTs) is a crucial step in assessing the tumours and providing patients with the most appropriate treatment options. MRI is one of many imaging techniques used for BT detection; it is preferred due to its higher image quality and the practical necessity of relying on non-ionizing radiation. The research by Rizwan et al. [2] recommended a Gaussian Convolutional Neural Network (GCNN) on two datasets to identify different kinds of BT. Tumors are categorized as pituitary, glioma, or meningioma in one of the datasets. The other divides Grade 2 gliomas from Grade 3 gliomas and Grade 4 gliomas. T1-weighted complexity enhanced photos show 233 and 73 victims in the first and second datasets, respectively, with a total of 3064 and 516 images, respectively.

Despite its importance and widespread necessity, brain image categorization remains a formidable scientific challenge. In this research, Al-Saffar et al. [3] introduced mutual information-accelerated singular value decomposition, a novel approach to feature selection for classifier input (MI-ASVD). Using this cutting-edge algorithm, the author developed a smart system that can distinguish between normal, high-grade glioma, and low-grade glioma in MRI brain pictures. Pre-processing, clustering, tumour identification, feature extraction, MI-ASVD, and classification are the six phases that make up the proposed system. To begin, enhancing techniques like Gaussian kernel filters are used to soften the MR pictures. The data is then sent into a clustering algorithm called local difference in intensity-means to identify anomalous areas. Tumor features are extracted using grey-level run-length matrix (GLRLM) features, texture features, and colour intensity features. Afterwards, the most helpful characteristics for the classification process are chosen using a specialized method that combines feature selection and dimensionality reduction, called MI-ASVD. In order to properly categorize the MR brain images, a simpler residual neural network method is finally applied.

Internet of Medical Things (IoMT) is bringing the healthcare system into the future online world, according to researchers in the field. The Internet of Medical Things (IoMT) enables computer-aided diagnostic (CAD) systems, which keep patients' medical records online and offer them supplementary data. With the proliferation of internet-connected smart gadgets, patients can now consult with doctors remotely about serious conditions like brain tumours, using an IoMT-based remote healthcare system. Tumors are often precancerous conditions that have a poor prognosis. Hence, many lives can be saved with the prompt diagnosis and categorization of cancers. A CAD system that is IoMT-enabled is crucial to resolving these issues. The last several years have seen a surge of interest in deep learning, a relatively new subfield of Machine Learning. Convolutional Neural Networks (CNNs) are a popular tool in this area of study. In this article, Sekhar et al. [4] used a transfer learning model to categorize brain cancers into three subtypes: glioma, meningioma, and pituitary. Pre-trained CNNs are used to extract information from brain MRI scans.

Brain tumours, both malignant and benign, are analyzed by doctors all around the world utilizing a computer-aided diagnosis technique. Radiologists often turn to AI-assisted image analysis and interpretation tools. In the classroom, a number of machine learning methods have been deployed, most of which focus on dividing an imaging modality into two classes, normal and abnormal, or on distinguishing benign from malignant tumours. Nonetheless, further effort is needed to accurately categorize these tumours into their respective malignancy classes. The goal of the proposed research is to classify different kinds of aggressive brain tumours performed by Vidyarthi et al. [5]. Five types of actual data on malignant brain tumours are used in this analysis. The extracted region of interest is analyzed using the suggested technique, which employs a large feature set from six domains. The Cumulative Variance technique is a newly proposed feature selection process that is used to select relevant features from the feature set pool (CVM). Next, K-Nearest Neighbor (KNN), multi-class Support Vector Machine (mSVM), and Neural Network (NN) models are trained and tested using the selected characteristics to forecast multi-class classification accuracy. The proposed feature selection approach is used in conjunction with three different classifiers to conduct the trials.

Radiologists have a formidable challenge when attempting to classify brain tumours due to the diverse characteristics of their malignant cells. Lately, computer-aided diagnosis methods have shown promise as a helpful technology for identifying brain tumours via MRI. Newer applications of pre-trained models typically extract information from deeper layers, which is where the differences between natural and medical images become most apparent. Noreen et al. [6] provided a strategy for early identification of brain tumours that involves the extraction and concatenation of many features at different levels. There are two deep learning models, Inception-v3 and DenseNet201. These two models were used to compare two situations for identifying and categorizing brain tumours. To begin classifying brain tumours, characteristics from several Inception modules were retrieved from a previously trained Inception-v3 model and then combined. Then, the softmax classifier was used to categories the tumour in the brain. Second, features were extracted from different DensNet blocks using pre-trained DensNet201. These merged features were then fed into a softmax classifier to determine the type of brain tumour. The publicly accessible three-class brain tumour dataset was used to assess both cases.

Brain tumours are particularly dangerous because they can grow to an incurable state if caught too late. An accurate diagnosis of a brain tumour is crucial for beginning the correct therapy, which in turn decreases the patient's likelihood of dying from their diseases. In recent years, a deep learning-based classification approach has gained widespread use for detecting brain tumours in 2D MR scans. Many deep learning approaches based on transfer learning are compared by Ahmad et al. [7], with a variety of conventional classifiers used for the brain tumour detection task. The study's findings are based on tagged photographs of both healthy and diseased brains. VGG-16, VGG-19, ResNet50, InceptionResNetV2, InceptionResNetV3, Xception, and DenseNet201 are just few of the seven approaches utilized for transfer learning. Support Vector Machine, Random Forest, Decision Tree, AdaBoost, and Gradient Boosting are the five classic classifiers that come next. Accuracy, precision, recall, F1-score, Area under the Curve, Jaccard Index, and Specificity are among the metrics used to assess the effectiveness of various feature extractor and classifier configurations based on deep learning. The combinations with the highest accuracy were then given together with their respective learning curves.

Quantitative brain analysis and the detection of brain diseases using multi-modal MRI benefit from accurate volumetric segmentation of brain tumours and tissues. However, 3D Fully Convolutional Networks (3D FCNs) employing simple multi-modal fusion techniques have a hard time picking up on the complicated and nonlinear complimentary information between modalities because of the intricate nature of the link between them. Meanwhile, volumetric feature misalignment in 3D FCNs is straightforward due to the indiscriminate feature aggregation between low-level and high-level features. Yet, the 3D convolution processes of 3D FCNs are often ineffective at capturing global relations between distant regions in volumetric images, despite being great at modeling local relations. In order to address these concerns, Zhuang et al. [8] presented an Aligned Cross-Modal Interaction Network (ACMINet) for tissue and tumour segmentation in MR images of the brain. First, an adaptable and efficient module for fusing and refining multi-modal characteristics was developed in this network. Second, the author created a volumetric feature alignment module that uses a learnable volumetric feature deformation field to dynamically align low-level and high-level features. Finally, the author presented a module for graph-based global context modeling in space and time by use of a volumetric dual interaction graph.

When it comes to detecting and diagnosing brain disorders, MRI is a crucial tool. Using a hybridized machine learning algorithm, Deepa et al. [9] suggested a new approach to the classification of brain abnormalities in MRI scans. Extracting features, selecting features, and classifying them are all part of the proposed process. The texture features are derived from an obscure quantized extreme pattern based on intended directions. Clustering-based wavelet transform is proposed for extracting intensity characteristics. In order to do the shape-based extraction, regular shape descriptors are used. The firefly method, built on the MAP heuristic, is offered as a means of selecting features. In the end, a classifier based on a hybrid of support vector machines and random forests is used. High-grade tumours, low-grade tumours, acute strokes, and sub-acute strokes are distinguished in the MRI brain tumour and stroke images. In addition, three distinct areas, including edoema and tumour regions, are found in tumour detection.

3. Proposed Model

Tumors can be either benign or malignant depending on their characteristics. Cancerous tumours, on the other hand, are malignant because their defective cells spread and kill off healthy ones, whereas benign tumours do not spread [24]. Hence, after a tumour diagnosis, individuals with benign or malignant tumours require rapid recovery treatment. Professionals in the medical field are working towards a high degree of accuracy in their use of digital imaging techniques to study human brain tissues [25]. The brain is the primary command centre, managing vital functions such as body temperature, fluid balance, heart rate, memory, and emotion. The most up-to-date digital image scanning tool, such as MRI, is typically the first choice of medical professionals for diagnosing a tumour. Brain-related disorders like Parkinson's, Hydrocephalus, Alzheimer's, and stroke can also be detected by MRI imaging. The MRI method can take pictures of the brain's inner structure [26]. By providing more desirable contrast information on brain tissues, magnetic resonance imaging has become the standard approach and generally available tool for the diagnosis of brain tumours [27].

Understanding the mechanism of a brain tumour begins with its detection and classification. MRI based detection is a novel method of diagnostic imaging that aids the radiologist in locating the tumour. Manually testing the MRI pictures, however, is a time-consuming operation that requires specialized knowledge. Improvements in CAD, machine learning, and deep learning in particular now allow the radiologist to more accurately detect brain cancers [28]. With the help of ML applications in the medical imaging industry, the CAD process has been greatly enhanced. These methods improve the CAD system's ability to detect brain cancers with more precision. Features are extracted, selected, and classified using methods developed for machine learning. The tumour area is extracted from the human skull using a variety of feature extraction methods. These methods include thresholding, clustering, contour, and texture. Features are extracted from MRI images using these methods, with the most relevant features chosen via a feature selection procedure. To achieve high precision, it is necessary to extract features that contain substantial discriminatory information. Nevertheless, it is possible to exclude crucial details from the original image by means of features extraction.

By differentiating between the features of this algorithm and the two categories of data that need to be processed the missing data and the noisy data, the K-NN algorithm's feature dealing with incomplete data, where the problem of resolving the absence of data has been solved, has been investigated. After identifying the wrong information, the k-NN is used to develop one of the most effective attribution methods; each scenario must include an error. The enhanced KNN is derived from the most frequent values. Following data extraction, nominal values are chosen by considering the nearest neighbours of the recovered numerical values. When dealing with the data impacted by a large technique, it is impractical to disregard the instances that contain them, a simple approach that has been established after many research and the search for the optimum grade detection.

To eliminate inaccurate information, estimations are used to calculate the wrong numbers, but it's important to keep in mind that these characteristics are often intertwined and don't function independently. This allows us to better examine the qualities and establish the relationships between them. The primary goal of data reduction based on the primary database is to gather reliable smart data without data loss; by doing so, we will enhance data extraction while decreasing the amount of storage space needed; this makes the data simpler to process in the future. EKNN predicts the value of a new instance based on its classification into groups based on their neighbors. Data features are represented along the several dimensions into which the sample training is projected. The training sample categorization is used to partition this area. If a point's nearest k neighbors all share the same classification, then that point is labeled with that class. The proposed model framework is shown in Figure 2.

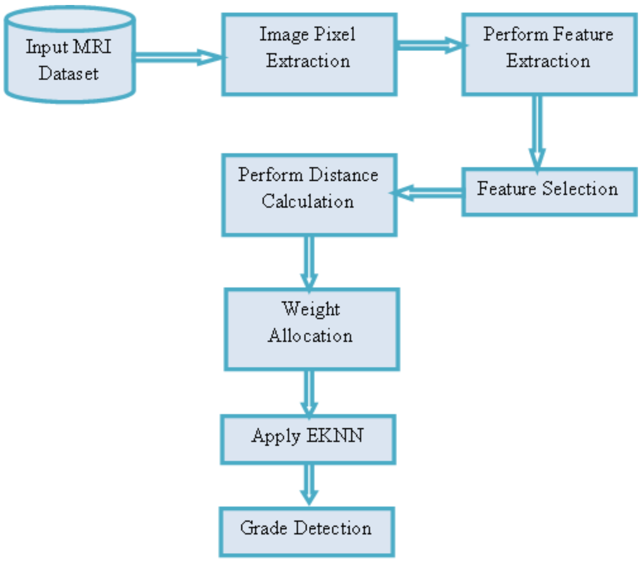

Fig 2: Proposed Model Framework

The purpose of classification is to place each data point into one of several categories. Classification is a crucial method extensively utilized to distinguish between healthy and malignant brain pictures. Classification is a data analysis process that involves building a model or classifier to make predictions about discrete labels. Classification is a data mining process that is used to place data points into predetermined groups. The purpose of classification is to make reliable predictions about which data cases belong to which target classes. The percentage value of comparing areas, coordinate areas of x and y, and labels obtained from training data all serve as inputs to the classification procedure. Training and actual classification are two distinct phases of the classification process. Certain portions of the training data are used to verify the precision of the data classification procedure. To aid doctors in the early detection of malignancies with accurate grade detection, a Multi Level Weighted Group Feature Set based Dissimilar Region Detection (WGFS-DRD) for accurate grade detection in brain tumor detection. This research makes use of WGFS-DRD based Enhanced K Nearest Neighbor (EKNN) model for accurate grade detection.

Calculating the test point's distance from each training point is a necessary step in the enhanced KNN algorithm. Hence, all the data in the training set is clustered into groups with similar samples. Splitting up the training data into smaller subsets significantly speeds up the computing process. The next step is to calculate the separation between the test point and the sub-set data point. The cluster centre is then used to identify the cluster to which the test point belongs. The centre of a cluster represents the average of its constituent data points. The dissimilarity is detected and the accurate grade is detected.

Algorithm WGFS-DRD

The brain MRI images are considered and the pixel extraction is performed from the images for accurate grade detection of brain tumor. The pixels extracted are used for processing and detection of tumor cells. The pixel extraction is performed as

$$Img[L] = \sum_{i=1}^{L} getImgattr(i) + getmaxIntensity(i) + \frac{\sum_{i=1}^{L} getminIntensity(i)}{getSize(i)}$$

Here getImgattr() is used to retrieve the RGB attributes of the current image I and L is the total images in the dataset, getmaxIntensity() is used to retrieve the image maximum intensity and getminIntensity(0 is used to get minimum intensity of the image

The pixel attributes are calculated by considering the maximum and minimum intensity levels of the image for detection of change in the pixel vectors that is performed as

$$\mathrm{PixSet}[\mathrm{L}] = \prod_{i=1}^{L} getmax\big(Img(i)\big) * \sqrt{\frac{\sum_{l=i}^{\mathrm{L}} (getImgattr(i)}{\mathrm{size}\big(\mathrm{Img(i)}\big)} + maxgreyrange(i) + Th}$$

Here maxgreyrange() gets the current image maximum grey level range that is from 0 to 255, Th is the threshold intensity value.

Data transformation into numeric values that may be processed without losing any of the original data's meaning is known as feature extraction. The features of the MRI image represent the main attribute set for detection of tumor cells. The process of extracting features is done as

$$Fset[L] = \sum_{i=1}^{L}\sum_{j=1}^{i} \mathrm{maxattr}\big(\mathrm{PixSet(i)}\big) + \frac{\prod_{i=1}^{L} \mathrm{minPixSetIntensity(j,i)}}{\mathrm{maxPixSetIntensity(j,i)}} + \mathrm{mean(PixSet(i,j))}$$

Feature Selection is a technique for streamlining the model's inputs by identifying and excluding irrelevant information. Automatic feature selection is the step in building a machine learning model in which features are selected automatically based on the nature of the problem being solved. The proposed model selects the most important features based on the extracted feature set using the minimum correlation factor and the process of selecting relevant features is performed as

$$Fset[L] = \sum_{i=1}^{L} maxRange\big(Fset(i)\big) * std\left(\mathrm{maxattr}\big(\mathrm{PixSet(i)}\big)\right) + \prod_{\mathrm{i=1}}^{\mathrm{L}} \frac{\mathrm{minRange}\big(\mathrm{Fset(i,i+1)}\big)}{\mathrm{size(Fset)}} + \mathrm{minCorr(Fset(i))}$$

The KNN technique was modified to become the EKNN technique. The core of this strategy is a system that uses neighbor pixel tags to categorize dissimilar test samples. This technique is a variant of weighted KNN, with the weights being calculated in a different way. The EKNN has an embedded learner that figures out how much importance to give each perspective in the selected features with allocated weights. In addition, the EKNN approach evaluates the significance of various viewpoints in identifying the unknown instance based on both the training data and the unknown instance itself. The EKNN is applied by selecting the nearest neighbor in the selected feature set as

$$mindist[Fset] = \sum_{i=1}^{L} \frac{minRange(\tau(i,i+1)}{size(Fset)} + T$$

τ is the model used for detection of Euclidean distance among the selected features, T is the threshold attribute in distance calculation.

The feature set is updated based on the weight allocation using the distance metrics. The features that are more relevant will be allocated with the weights for training the model. The weight allocation is performed as

$$Walloc[L] = \prod_{i=1}^{L} \frac{\sqrt{maxattr(corr(mindist(i,i+1))) - minattr(corr(mindist(i,i+1)))}}{\min(\tau)} * \frac{\max(\mathrm{Fset(i)})}{\mathrm{mindist(i)}}$$

Tumor dimensions and contours are determined by the verification of dissimilarity and the detection of dissimilar regions based on the feature vector updated with EKNN. The dissimilarity between the finalized attributes and the predicted grade is determined as

$$BTGrade[L] = \sum_{i=1}^{L} \max_{0\le i\le L} Walloc\big(Fset(i,i+1)\big) + \frac{simm(Walloc\big(Fset(i,i+1)\big))}{size(Img(i))} + \frac{minRange(\tau(i,i+1)}{\mathrm{mindist(i)}}$$

4. Results

One of the most lethal, destructive, and aggressive diseases that drastically cuts people's lives short is BTs. Individuals with BTs who are incorrectly identified or who are not given adequate medical therapy have a lower likelihood of survival. MRI is frequently used to evaluate tumours. However, manual segmentation in a fair amount of time is challenging due to the enormous data produced by MRI, which limits the implementation of standard criteria in clinical practice. The substantial temporal and structural heterogeneity of brain tumours is a challenge for automated segmentation and grade detection. Thus, early diagnosis and therapy are crucial. Several traditional machine learning techniques have been used for tumour and cancer detection in the brain. However, these models' primary weakness is the necessity of human intervention in extracting features.

The proposed model is implemented in python and executed in Google Colab. The dataset is considered from kaggle that is available from the link https://www.kaggle.com/datasets/navoneel/brain-mri-images-for-brain-tumor-detection. The Kaggle dataset has 3000 photos in total, 1500 of which are brain tumours with different grades and 1500 of which are healthy individuals without tumours. The minimum pixel size for every uploaded image is 224x224. To ensure the dataset was suitable for the proposed methodologies, it was subjected to preliminary processing. The suggested model was given input data consisting of images labeled 0 for normal and 1 for brain tumour detection. To aid doctors in the early detection of malignancies with accurate grade detection, a Multi Level Weighted Group Feature Set based Dissimilar Region Detection (WGFS-DRD) for accurate grade detection in brain tumor detection. The proposed model is compared with the traditional Maximum APriori (MAP) based Firefly Algorithm (MAPFA) model and the results are clearly indicated.

Feature extraction is used to describe the procedure of reducing unstructured data to a set of quantifiable characteristics that may then be processed without losing any of the original data's context. When using machine learning, the results are far more favorable. The Image Feature Extraction Accuracy Levels of the existing and proposed models are shown in Figure 3.

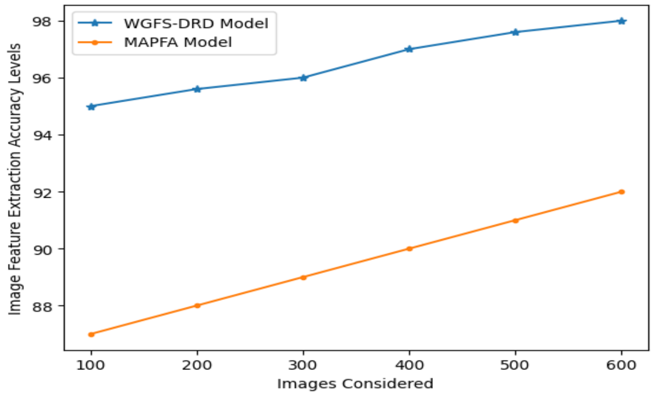

Fig 3: Image Feature Extraction Accuracy Levels

Feature Selection is a technique for streamlining model's inputs by identifying and excluding irrelevant information. Automatic feature selection is the step in building a machine learning model in which features are selected automatically based on the nature of the problem being solved. The Figure 4 represents the Image Feature Selection Time Levels of the proposed and existing models.

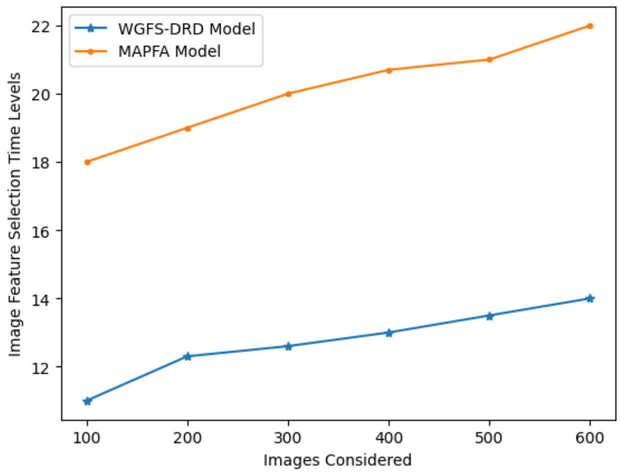

Fig 4: Image Feature Selection Time Levels

To the selected features, weights are allocated to set the priority for the features for training. The independent features are allocated with highest weight. The Feature Weight Allocation Accuracy Levels of the existing and proposed models are represented in Figure 5.

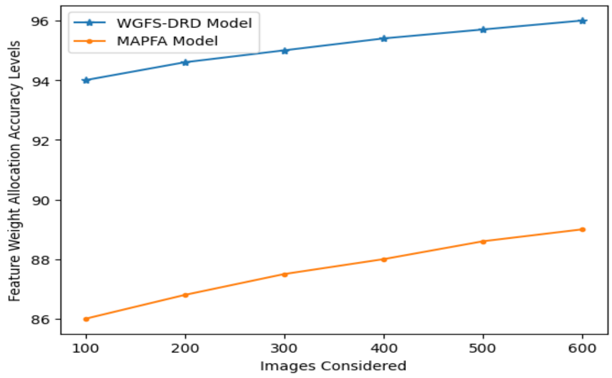

Fig 5: Feature Weight Allocation Accuracy Levels

The proposed model, based on the features selected, the dissimilar regions that contains tumor region is identified based on the training model. The Dissimilar Region Detection helps in accurate tumor region selection. The Figure 6 represents the Dissimilar Region Detection Time Levels of the existing and proposed models.

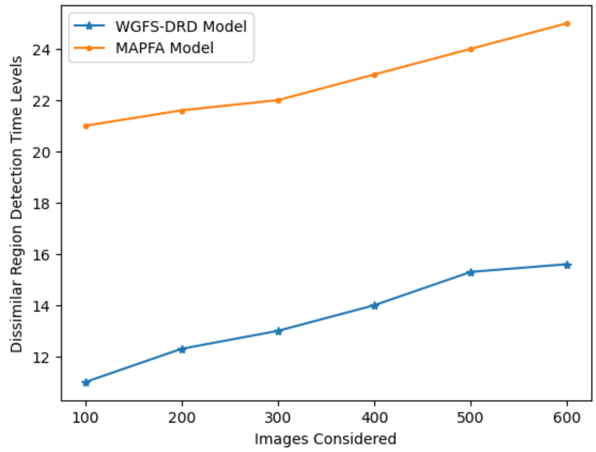

Fig 6: Dissimilar Region Detection Time Levels

The feature selection process is updated with removing some features from the selected list. The multi level weighted group feature set is used for tumor detection. The Multi Level Weighted Group Feature Set Generation Accuracy Levels of the existing and proposed models are shown in Figure 7.

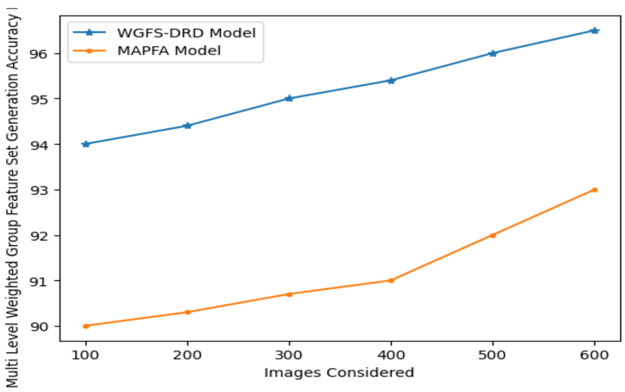

Fig 7: Multi Level Weighted Group Feature Set Generation Accuracy Levels

The MRI images are processed and the feature selection is performed. The model based on the training samples, performs the tumor detection in the MRI extracted features. The proposed model accurately detects the tumors in the MRI image. The Figure 8 shows the Tumor Detection Accuracy Levels of the proposed and existing models.

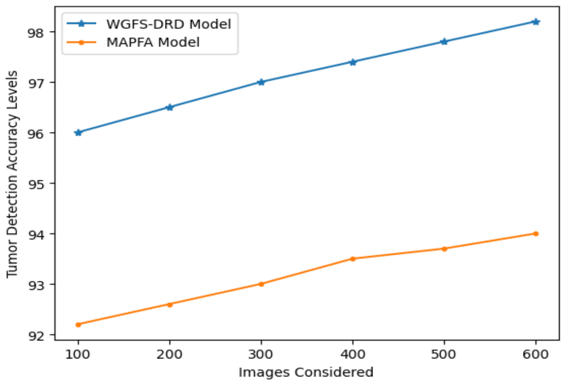

Fig 8: Tumor Detection Accuracy Levels

After detection of tumor in the MRI images, the tumor region is detected and the size of the tumor is identified. The size of the tumor based grade detection is performed that accurately detects the tumor size from the MRI images. The Figure 9 shows the grade detection accuracy levels of the proposed and existing models.

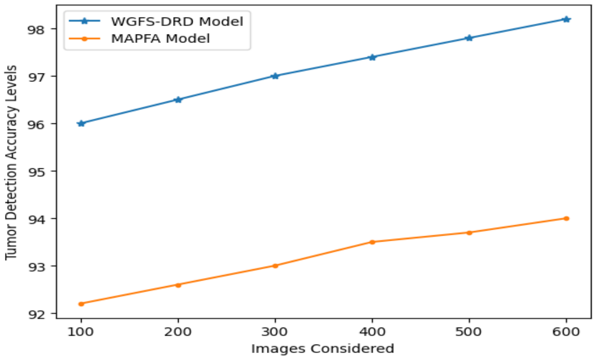

Fig 9: Grade Detection Accuracy Levels

5. Conclusion

The field of medical imaging has rapidly evolved into an integral part of modern medical practice. Automatic detection, which provides data on abnormalities for further treatment, relies heavily on it. The value of automating tumour identification as a means to save radiologist time is rising. Accurate diagnosis, treatment planning, and evaluation of treatment outcomes all depend on recognizing and correctly classifying brain tumours. Despite recent breakthroughs in medicine, histopathology diagnosis remains the gold standard for categorizing brain tumours. A conclusive diagnosis is typically reached by a combination of clinical signs and symptoms, imaging tests, and pathological examinations. This diagnostic process has a number of drawbacks, the most significant ones being that it is invasive, lengthy, and susceptible to inaccuracies in the samples it obtains. Computer-aided, fully automated identification and diagnostic equipment that aim to create rapid and correct judgments by professionals have the potential to boost the investigative capacities of physicians and radiologists and reduce the time required for a right diagnosis. To aid doctors in the early detection of malignancies with accurate grade detection, a Multi Level Weighted Group Feature Set based Dissimilar Region Detection for accurate grade detection in brain tumor detection. In this research, a WGFS-DRD based KNN algorithm that employs attribute weighting and grouping, and multi level distance weighting based on the results of the analysis is proposed. This proposed approach speeds up processing time while simultaneously increasing classification precision and grade detection accuracy levels. The proposed model achieves 98% accuracy in accurate grade detection that helps the medical experts to provide better diagnosis for the patients. In future, the proposed model can be enhanced by using hybrid machine learning models and optimization techniques can be applied for enhancing the precision rate. Deep Learning models can be applied for the enhanced precision levels.

Conflicts of interest

The authors declare no conflicts of interest.

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