A Novel Hybrid Deep Learning Framework for Detection and Categorization of Brain Tumor from Magnetic Resonance Images

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***Abstract*—Cellular abnormality leads to brain tumour formation. This is one of the foremost reasons of adult death all over the world. The typical size of a brain tumour increases within 25 days due to its rapid growth. Early brain tumour diagnosis can save millions of lives. For the purpose of early brain tumour identification, an automatic method is necessary. MRI brain tumour detection improves the survival of patients. Tumour visibility is improved in MRI, which facilitates subsequent treatment. To distinguish between brain MRI images with tumour and images without tumour is suggested in this paper. Many approaches in the field of machine learning including Support Vector Machine, Artificial Neural Networks, and KNN classifier have been developed for solving these issues. But these methods are time consuming, inefficient and require complex procedures. For a Computer Assisted Diagnosis system to aid physicians and radiologists in the identification and categorization of tumours, artificial intelligence is used. Deep learning has demonstrated an encouraging efficiency in computer vision systems over the past decade. In this paper, identification and classification of brain tumour from MR images employing BGWO-CNN-LSTM method is proposed. The proposed method on a testing set with 6100 MRI images of four different kinds of brain tumours is utilized. In comparison to earlier research on the same data set, the suggested approach achieved 99.74% accuracy, 99.23% recall and 99.54% specificity which are greater than the other techniques.**

***Keywords*—Brain tumour; BGWO; LSTM; CNN; MRI dataset**

I. INTRODUCTION

The brain is a massive, intricate part that governs the entire nervous system in humans and comprises an estimated hundred billion nerve cells. This vital organ was grown in the brain's cerebral cortex. As a result, any brain abnormalities could be dangerous for people's health. Brain tumours are among the most serious of these disorders [1]. For the proper operation of the human body, the majority of the cells which are produced in the body split to become new cells. Older or damaged biological cells expire as new ones proliferate. New cells then replace the old ones. Occasionally, when the body does not require them, new cells are produced. Extra cells produced in the body build a form of tissue known as a tumour. The delicate bodily functioning is distorted by a tumour positioned in the brain area. Due to its position and tendency to spread, it is extremely dangerous and difficult to cure [2]. Tumors can be classified as either cancerous as well as non-cancerous. Both benign and malignant brain tumours are recognized as dangerous conditions. The tumour spreads throughout the skull, flattening the other development. Primary tumours and secondary tumours are the two different categories of brain tumours. The primary tumour arises in the tissues of the brain, and the secondary tumour spreads from other body regions to the skull [3]. Pituitary tumours, gliomas and meningiomas are a few kinds of primary brain tumours. Tumors that form in brain tissues apart from nerve cells and blood vessels are referred to as gliomas in context. Pituitary tumours are lumps that reside within the skull; however meningiomas safeguard and surround the central nervous system and the brain. [4]. The meninges covers the brain within the skull, is where meningioma tumours first appear. These tumours are benign because of their sluggish growth. The malignant tumours known as gliomas begin in the brain, spinal cords, and nearby glial cells, which are nerve cells [5]. Developing an efficient therapy for brain tumours depends on an early and precise diagnosis of the condition. The pathologic grade, type, and tumour stage at the point of diagnosis significantly influence the treatment mode selection [6]. A significant aspect of investigation in the range of medical imaging is early detection and categorization of brain tumours, which helps doctors choose the most practical way to proceed to rescue patient's lives [7].

For instance, doctors may employ radiation, surgery or chemotherapy to treat tumours. However, it always relies on the shape, nature, and size of a tumour. Clinically relevant

technology, such as Magnetic Resonance Images, produces extensive information on tumour and normal regions in the type of their slices. Furthermore, not all slices can be seen as tumours with the naked eye of a human. Therefore, correct assessment of a brain tumour necessitates the use of a skilled radiologist. Therefore, in order to identify a tumour in MR images without the use of humans, automated machines are always necessary [8]. The categorization of brain tumours has been approached from a variety of perspectives [9]. The investigators convey a variety of strategies, including super pixel-based brain tumour segmentation, multifractal features, salient structural topographies with RBF SVM kernel, and clustering-based segmentation with SVM[10]. ML methods rely on manually created characteristics, which limit the method's resilience. The efficiency of the deep learning-based algorithms, however, is substantially greater because they dynamically identify useful characteristics [1]. The current automated and semi-automated disorder analysis procedure's main goal is to create a reliable disease recognition system to help the physician with diagnosis and treatment planning [11]. The majority of image processing methods are utilized for tumour diagnosis. The goal of segmenting the image is to divide an image into uniform districts, thereby identifying the structures of the district [12]. The Magnetic Resonance Images plays an integral role in sophisticated research studies of the human brain. Magnetic Resonance scans may reveal important details about the composition of soft tissue. Additionally, the superiority of diagnosis and brain pathology are significantly enhanced by Magnetic Resonance imaging [3]. A doctor performs a biopsy to screen for tumours by taking a lesser sample of tissue and examining it under a microscope. Even though a biopsy can detect abnormalities with accuracy, people usually experience pain throughout the procedure. Second, doctors must be cognizant of the precise position and size of the tumour before doing surgery [13]. Therefore, MRI or CT scans are the most common approaches for evaluating the structure of a brain tumour. Nevertheless, MRI provides an accurate view of the structural development of brain tissues, whereas CT scans expose people to radiation that is harmful to their health [2].

Traditional ML strategies for categorization tend to concentrate on only limited or elevated features employ some manually created features to close these gaps, and call for effective feature extraction and categorization procedures. Deep CNNs, a recent innovation in DL, have attained achievement in the categorization of images [14]. Nowadays, a significant part of investigation in the health care zones is the automated recognition and segmenting the organs on medical images. There have been several techniques created that cover all geographical localizations and imaging modes. These researches, which make use of complicated blob-based algorithms, shared a recognition rates that seemed hard to enhance without complicating the feature extraction techniques significantly. Additionally, DL methods outperform typical machine learning techniques, which are constrained in their ability to analyse visual features in their natural form, time-consuming, dependent on professional expertise, and demanding a lot of work for parameter tuning [15].

In this study, three pathogenic categories of brain tumours precise and automatic categorization system including glioma, meningioma and pituitary tumour was provided. For extracting the features from brain MRI images, the remedy makes use of deep transfer learning model CNN [6]. It can be used in a variety of fields, such as object recognition, speech recognition, and image categorization. The DL mechanism is frequently utilized with CNN because it makes it simple to handle the hidden, input, and output layers [16]. Utilizing tested classifiers, the collected characteristics are categorised. Next, a thorough assessment of the suggested system is made. When tested on the open dataset, the suggested system outperformed all similar research in terms of classifier performance. Additionally, the suggested approach is found to deliver respectable results with fewer training data [6].

The following is a list of this article's main contributions:

- The system begins by collecting and processing a large set of input images using an MRI dataset.
- A Gabor filter is then employed to further analyze the input images that were generated.
- The impacted portion is then segmented through Otsu thresholding.
- A hybrid optimization technique combining the Bat and Grey Wolf performs feature extraction.
- After that, classification is carried out with the CNN-LSTM model.
- The efficiency of the developed approach is then verified and contrasted with those of other pre-trained models.

The residue of the article is arranged as follows: Section II deliberates the closely related studies. The proposed method, block diagram, flowchart and algorithms are thoroughly summarized in Section III. In Section IV, the experimental method of the suggested brain tumour categorization and recognition system is covered in detail. Section V illustrates the research findings and contrasts them with existing systems. The conclusion is organized in Section VI.

II. Related Work

Jaeyong Kang et al. [1] introduced a technique for categorising brain tumours using a combination of deep features and ML classifiers. The idea of transfer learning and various pre-trained DCNN are employed in this suggested framework to collect deep features from brain MRI. Different machine learning classifiers subsequently examine the deep features that were gathered. An ensemble of deep features consisting of the top 3 deep features that consistently outperform other machine learning classifiers is chosen, combined, and utilized to determine the result. Three distinct brain MRI datasets which are freely accessible are employed to compare the performance of machine learning classifiers, deep feature extractors, and an ensemble of deep features for the categorization of brain tumours. However in some circumstances, the Support Vector Machine with Radial Basis Function (RBF) kernel surpasses conventional ML classifiers, mainly for large datasets. According to experimental

observations, this method suggests that an ensemble of deep features can greatly increase efficiency. Even though our suggested strategy performs well, more research is required to minimize the model's structure so that it can be implemented on an actual medical diagnosis process utilizing knowledge filtering techniques. Siva Raja and Antony Viswasa rani [3] created a combined deep auto encoder with a Bayesian fuzzy clustering (BFC) method that is based on segmentation to categorize brain tumours. The non-local mean filter is originally utilized in the pre-processing phase for noise elimination purposes. Then, the BFC technique is employed to separate brain tumours. Following segmentation, reliable attributes are collected by utilizing Wavelet Packet Tsallis Entropy and Scattering Transform techniques. In order to categorise the tumour component for the brain tumour classification procedure, a combined strategy of the DAE oriented Jaya optimization algorithm combining softmax regression method is used. A MATLAB framework is applied to perform the suggested strategy. In comparison to other techniques, the simulated outcomes from the BRATS 2015 database demonstrated that the suggested strategy acquired a significant amount of classification accuracy of 98.5%. However, the more prevalent technique that will be employed to enhance the accuracy by combining more than one classifier based on the huge library of medical images and the precise classification strategy is not discussed.

Shahariar Alam et al. [2] presented a mechanism for identifying human brain tumours in an MRI image that combines the template-based K means and enhanced fuzzy C means (TKFCM) algorithms. Initially, the template-based K-means method is employed in this suggested technique to effectively choose a template created on the gray-level intensity of the image, which greatly initialises segmentation. Eventually, the enhanced FCM clustering method is employed for sensing tumour place by upgrading membership function that is derived on the basis of the characteristics of tumour images such as Energy, Homogeneity, Correlation, Dissimilarity, Entropy and Contrast. The revised membership is calculated by the cluster centroid distances to cluster data points by employing the Fuzzy C Means algorithm that gives better outcomes. According to simulated outcomes, the suggested technique is more effective at identifying diseased and normal brain tissues with only a slight loss in gray-level intensity. Additionally, compared to other techniques, this method predicts human brain tumours in a matter of seconds. However, the accuracy is left undiscussed. Rupa Ezhil Arasi and Suganthi [17] suggested a Soft Computing techniques of Clinical Support System for Classifying Brain Tumours. The brain MRI image is pre-processed by applying Genetic Optimized Median Filter in the presented Clinical Support System, and then the brain tumour zone is segmented by applying Hierarchical Fuzzy Clustering Technique. The GLCM feature extraction approach is utilized to capture the characteristics of the tumour region. The Brain Tumour Image Segmentation dataset is employed to accurately classify the tumour using the Lion Optimized Boosting Support Vector Machine method. As a result, the suggested clinical support system provides a comprehensive framework for the recognition and categorization of brain tumours, assisting the physicians in a proper assessment of the tumour. The findings show that the suggested approach accurately categorises the tumour with a 97.69% accuracy rate. The primary benefit of the suggested approach is that it also evaluates tumour size and identifies the forms and phases of tumour. However, diagnostic errors are not recognized.

In order to improve images, Muhammad Sharif et al. [18] introduced a triangular fuzzy median filtering that supports in precise segmentation utilizing an unsupervised fuzzy system technique. In this method, Similar texture (ST) features are validated by utilising retrieved Gabor features over each person's tumours. Extreme learning machine ELM obtains these similar texture behaviours, and the reduction ELM omits one for tumour classification. On the BRATS 2013, 2012, 2015, 2014 datasets and on the 2013 Leader board, the method is tested. The suggested method yields superior outcomes and requires less computing time. However, managing distorted images and segmentation precision is not improved. Javaria Amin et al. [19] developed an innovative method on the basis of LSTM technique and MRI is offered to address the issues with automatic brain tumour categorization. To enhance the image quality of the multi-sequence MRI, N4ITK and 5×5 sized Gaussian filters are first utilised in this approach. The 4 layer deep LSTM framework is typically provided for classifying. The best hidden units including 200 HU and 225 HU are taken for every layer. In order to achieve superior outcomes, these disguised or hidden components were selected after intensive experimentation. The SISS-ISLES 2015 dataset and various BRATS dataset variants are employed to validate the findings. The approach was also tested using actual brain tumour patients from Pakistani ordinance factories, with a 0.97 DSC. The outcomes show that the proposed strategy gives radiologists additional assistance in accurately classifying brain tumours. The suggested technique had an accuracy rate of up to 98%. However, classifying subtumoural region and measuring the severity level of tumour region is not discussed.

Shah Rukh Khan et al. [13] introduced a Partial Tree, an association rule classifier with a sophisticated characteristic set to identify brain tumours according to their grade. The suggested method is evaluated by applying a 10-fold cross-validation procedure, and it is contrasted with other mechanisms including Random Forest, CART, Naïve Bayes and Random Tree. In this technique, threshold segmentation and masking are performed to magnetic resonance images as pre-processing processes prior to feature extraction. Depending on the grey level of the pixels, threshold segmentation isolates them into different sections. An intensity value called as the threshold determines categorization. The outcomes demonstrate that a partial tree with an enhanced feature set outperforms the existing approaches. Additionally, certain more sophisticated features should be utilized to boost performance. Arunkumar et al. [20] developed a new method of segmenting brain tissues from Magnetic resonance images. The main vision - based simulation methodologies utilized in the method are image segmentation, non-ROI filtering and image enhancement on the basis of texture and HOG features. ANN is employed in a fully automated framework technique for MRI brain tumour segmentation and categorizing to accurately pinpoint the

ROI's position. In order to evade non ROI and choose the exact object in brain MRI, the filtering out non ROI technique has been employed in perspective of histogram analysis. Nevertheless, using the textural features can determine the type of tumour. For the comparison of the automated and human segmentation processes, 200 MRI samples are employed. The results analysis proves that fully automatic model on the basis of trainable segmentation outperforms traditional methods and ROI texture-based brain diagnosis. 92.14% accuracy in diagnosis was recorded, with 94 specificity and 89 sensitivity. However, the brain trainable segmentation challenge was frustratingly difficult because of the enormous variability in brain tumour size and position in the images.

Bahadure et al. [21] introduced a comparative methodology on the basis of magnetic resonance images of brain tumour Segmentation and categorization by applying genetic algorithm. In this method, various segmentation strategies are compared to enhance the efficiency of tumour identification, and the better segmentation methodology is chosen by contrasting their segmentation scores. Additionally, the genetic algorithm is utilized for the automated identification of tumour stage in order to increase accuracy rate. Extraction of pertinent features and region computation assist the categorization phase choice. Depending on sensitivity, accuracy, specificity, segmentation score and dice similarity index coefficient, the study outcomes of the suggested methodology are assessed and verified for both quality and performance assessment on MR brain images. The experimental outcomes averaged a dice similarity index coefficient of 93.79%, indicating improved overlapping between radiologists' subjectively and automatically derived tumour regions. However, the discussion about a research of reliable technique for the huge medical image database and a discriminating classifier strategy by integrating more than one classifier is not recognized. Diaz-Pernes et al. [22] introduced a fully automatic brain tumour segmentation and classification technique that employs use of a multiscale DCNN. The functioning of the human visual system aided as motivation for this approach. The proposed neural framework is capable of performing tumor-specific MRI image analysis. The technique's efficiency on a dataset of 3064 MRI image slices from 233 patients that is publicly visible is contrasted with other traditional ML and DL approaches. In the assessment, this approach significantly performed with a tumour classification accuracy of 0.973. This technique helps doctors to diagnose brain tumours, and the presented segmentation and categorization technique can be utilised to solve various imaging issues in the field of medicine. However, it is not explained how the suggested multiscale CNN for segmentation could be applied to other research areas, like satellite imaging.

The aforementioned literature review provides a clear picture of the techniques that have been developed, the more common technique that will be used to increase accuracy by combining multiple classifiers based on the vast library of medical images, and the precise classification approach are not included, and diagnostic errors that are not recognized. There is no discussion of classifying the sub tumoural region or determining the tumor location's severity level. The huge variation in size and location of the brain tumors in the images made the brain trainable segmentation problem painfully challenging. To solve these problems, the BGWO-CNN-LSTM approach is suggested in this study for the detection and classification of brain tumors using MR images. The observations support the assertion that the suggested strategy makes it simple for clinical experts to make decisions about diagnosis and scanning.

III. PROPOSED METHODOLOGY

The presentation is the automatic process for the lesion and imaging stages of brain tumour identification. MRI tests are done on the proposed system. As a result of its high contrast, spatial resolution, and low radiation MRI seems to be more effective at detecting tumours. The location and size of a brain tumour can be determined by MR scans [12]. The presented approach contains five main steps: image acquisition, pre-processing, segmentation of images, feature extraction and classification. Various methodologies are used during pre-processing to split the region of interest. The Gabor filter is utilized for the pre-processing stage. The next phase is image segmentation, where the normal and abnormal regions are separated using K means clustering. Next, the feature extraction is done by applying Bat and Grey Wolf Optimization (BGWO) algorithm. Finally, CNN-LSTM is utilized for classification. The developed method is outlined in Fig. 1.

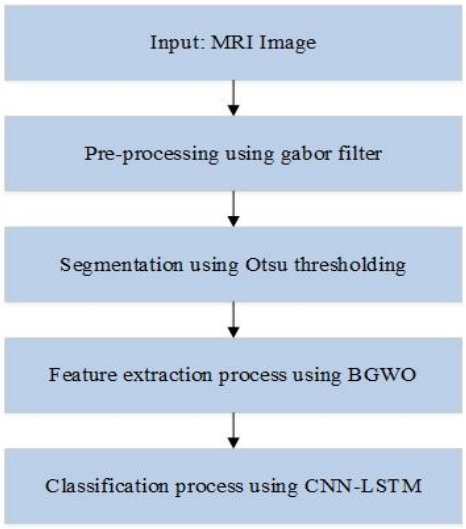

Fig. 1. Overall process of the developed method.

A. Data Collection

The effectiveness of the developed detection system relies on the database that is utilized in every medical assessment operation. The dataset utilised in this research was obtained from BRATS 2015 that contains a distinct version of BRATS that is designed to address medical imaging challenges. The BRATS 2015 imaging dataset, that can display an upgraded form of new cases reported with greater efficiency, was derived from BRATS 2012 and BRATS 2013 [16]. The dataset contains 6100 MRI images of the human brain that are categorized into 4 categories: meningioma, pituitary, glioma,

and normal. The dataset is splitted into 80% of training data and 20% of testing data. The description of database is shown in Table I.

TABLE I. DATASET DESCRIPTION

Disease type	Training data	Testing data	Total
Pituitary	1205	195	1400
Meningioma	1327	473	1800
Glioma	534	366	900
Normal	1602	398	2000

B. Pre-processing

The brain MRI datasets entirely contain unwanted gaps and areas, which leads to inadequate categorization accuracy. Therefore, it is vital for image cropping to eliminate unnecessary portions and use relevant data. The cropping approach is applied for calculating extreme points. For pre-processing, import the primary MR images. Then, in order to create binary images, perform thresholding to the MR images. In this research, Gabor filter is applied. When the Gabor filter is utilized for texture features, it effectively examines if the image contains any particular frequency information or particular directions in a restricted region around the pixel or region of evaluation. Gabor filters are utilized in the study of multi-resolution images which is like human vision cortex since every filter exhibits a sensory neuron which is responsive to a certain frequency. This is because of the band-pass nature and chosen direction qualities of Gabor filters [18].

Gaussian function in the $f(a,b)$ domain's spatial coordination is defined using the Gabor filter. Assume the Fourier transform of $f(a,b)$denoted by *F (m, n)* that is a function of the frequency components *(m, n)* given in Eq. (1).

$$f(a,b,\sigma,\beta) = \left(\frac{1}{2\pi\sigma_a\sigma_b}\right) exp\left[-\frac{1}{2}\left\{\frac{a^2}{\sigma^2}\right\} + 2\pi r\beta a\right] \quad (1)$$

In the Gabor filter, the Gaussian window is adjusted by σ among the appropriate axis while the Gaussian function is combined in the Fourier domain. β represents the Gabor filters' centre frequency. The filter results are displayed in Eq. (2) with a good response at the frequency centre.

$$K(\mu,w,\sigma,\beta) = exp\left\{-\frac{1}{2}\left(\frac{(\mu-\beta)^2}{{\sigma_\mu}^2} + \frac{w^2}{{\sigma_w}^2}\right)\right\} \quad (2)$$

Where $\sigma_\mu = \frac{1}{2\pi\sigma_a}$ and $\sigma_w = \frac{1}{2\pi\sigma_b}$

C. Segmentation using Otsu Thresholding

After pre-processing, Otsu thresholding is utilized for segmentation process. Otsu is an automated threshold selection technique for segmenting data depending on region. Gray levels are used in the unsupervised, nonparametric Otsu threshold method. Otsu threshold criterion utilises an image's gray-level histogram, and the threshold procedure determines a normalised value in the [0, 1] range [23]. The probability distribution is represented in Eq. (3).

$$a(t) = \frac{h_t}{H} \quad (3)$$

Where, $a(t)$ is the probability distribution, *H* represents the total no. of image pixels, and *h* is the histogram count for pixel value *t.*

Eq. (4) and (5) employ the probability distribution $a(t)$to derive the class probability. Every image pixel is divided into the classes of background and object, with a threshold, separating them. The class probability is expressed as,

$$u_0 = \sum_{m=1}^{l} a(t) \quad (4)$$

$$u_1 = \sum_{m=l+1}^{k} a(t) \quad (5)$$

Following, the class mean which is denoted by μ is represented as,

$$\mu_0 = \sum_{m=1}^{l} \frac{ta_t}{u_0} \quad (6)$$

$$\mu_1 = \sum_{m=l+1}^{k} \frac{ta_t}{u_1} \quad (7)$$

Eq. (6) and (7) are substituted in Eqns. (8) and (9), respectively.

The following equations are employed to form the class variance equation:

$$\sigma_0 = \sum_{m=1}^{l} [t-\mu_0]2\frac{a(t)}{u_0} \quad (8)$$

$$\sigma_1 = \sum_{m=l+1}^{k} [t-\mu_1]2\frac{a(t)}{u_1} \quad (9)$$

The formula for weighted within-class variance is illustrated in Eq. (10)

$${\sigma_u}^2 = u_0{\sigma_0}^2 + u_1{\sigma_1}^2 \quad (10)$$

Where, u_0 is the weight of the background, u_1 is the weight of foreground, σ_0 is the variance of background and σ_1 is the variance of the foreground.

The performance of segmenting the brain tumour is evaluated through the performance rate after the Otsu approach is applied to the synthetic image which is given in Eq. (11).

$$Performance = \frac{No.\ of\ pixels\ of\ object\ after\ segmentation}{No.\ of\ pixels\ of\ object\ before\ segmentation} \quad (11)$$

Generally, a successful segmentation of an image occurs when all of the object's pixels are separated from the background without any additional or subtracted pixels. When segmenting an image, the performance is less than 1, which suggests that some pixels related to the object were mistakenly categorised as background and object. If the rate of performance is 1, then an object's pixels have all been completely segmented.

D. Feature Extraction and Selection using BGWO Algorithm

1) Bat optimization algorithm: A meta-heuristic search technique called the BAT algorithm [24] imitates the action of bats. This optimization method utilizes the echolocation system of bats to find food and distinguish it from other objects. Bats make quick, loud pulses that detect an echo and return to their ears. BAT determines the distance, kind of

object and the time it takes for it to return. The bat's position and velocity matrices, a and p, are updated by bat algorithm in the d-dimensional search area is represented in Eq. (12) [25].

$$a_m^l = a_m^{l-1} + (p_m^{l-1} - p_{best}) \times g_m \quad (12)$$

Where *l* is the current iteration, and p_{best} is the best global solution.

2) Grey wolf optimization algorithm: The grey wolf optimizer (GWO) method [26] is a swarm-based method that derives from nature and imitates the hierarchical society of wolves and their behaviour in encircling, approaching and attacking the prey. The grey wolves social behaviour during the hunting process is portrayed statistically to solve an optimization issues by applying the GWO algorithm. The wolves in GWO iterations assess the potential hunting circumstances and revise their status as necessary. The encircling process' mathematical expression is given by,

$$\vec{G}(s+1) = \overrightarrow{G_a}(s) - \vec{P} \times \vec{R} \times \overrightarrow{G_a}(s) - \vec{G}(s) \quad (13)$$

In the equation preceding, *s* stands for the current iteration, $\overrightarrow{G_a}$ and $\vec{G}$ stand for the hunt and hunter position vectors and $\vec{P} = 2\vec{p}.\overrightarrow{c_1} - \vec{p}$ and $\vec{R} = 2\overrightarrow{c_2}$ stands for coefficient vectors. $\overrightarrow{c_1}$ and $\overrightarrow{c_2}$ are random numbers between 0, 1 that permit the wolves change their position in the hunt space. The best exploration factor equation is represented in Eq. (14)

$$\vec{G}(s+1) = \frac{\vec{G} + \overrightarrow{G_2} + \overrightarrow{G_3}}{3} \quad (14)$$

A novel hybrid combination of BGWO using the fitness values is given in Eqn. (15),

$$a_m^l = a_m^{l-1} + (p_m^{l-1} - p_{best}) \times \vec{G}(s+1) \quad (15)$$

E. Classification

1) Convolutional neural network: The CNN is the deep neural network. It aims to discover the underlying and intrinsic characteristics from guided processing of 2-Dimensional or 3-Dimensional images. These characteristics are suitable for classifying anatomical structures and identifying aberrant structures. An input layer is associated with a number of pooling layers, output layer and convolutional layer in a standard CNN architecture.

a) Convolutional layer: The convolutional layers perform a convolution operation by using convolution kernels and the raw input data to create new attribute values. The model was developed to collect features from dataset images, so the input data should be in the procedure of structured matrix. When compared to the input matrix, the convolution kernel is comprehended as a narrow window that organises coefficient values into a matrix. This window "slides" around the input matrix, performing a convolution process on every patch while moving. A convolved structure, is a feature variable established by the coefficient values and the allocated dimension element of the filter. Convoluted features which are often more useful than the principal features of the input data can be produced by applying various convolution kernels to the input data. Hence, the approach performs better. The basis of a CNN is a convolutional layer, because the majority of computations are completed at this layer. It is a quality extraction layer that pulls out the regional features via the filters and produces a convolutional calculated feature map and exits the kernel function and goes to the pooling layer. The convolutional layer is expressed in Eq. (16).

$$P_m{}^{(a)} = \sigma(G_m{}^{(a)} + \sum_{n=1}^{s(a-1)} P_n{}^{(a-1)} * U_{m,n}{}^{(a)}) \quad (16)$$

Where the operator * denotes the convolution operation, σ is an activation matrix, and $U_{m,n}{}^{(a)}$ is the filter linking the n^{th} feature map in layer *a*-1 with the m^{th} feature map in layer *a* is a function that is employed to increase nonlinearity.

b) Pooling layer: Typically, the pooling layer is applied following the convolutional layer. The pooling layer's job is to streamline the data in the output of the layer of convolution. The pooling layer creates a compressed feature map using each feature map's data from the convolutional layer. The most popular techniques are max-pooling and average pooling. There is no learning happening in this tier. Size NxN filters have been chosen in this layer. The average pooling and max pooling layer is represented in Eq. (17) and (18).

$$\bar{a} = \frac{1}{L}\Sigma_{(m,n)\in G} a_{m,n} \quad (17)$$

$$a_{max} = max_{(m,n)\in G}(a_{m,n}) \quad (18)$$

Where $a_{m,n}$ is the number of each pixel in area *G* and *L* is the area's pixel count.

c) Dense layer: In Dense layer, the Long-Short Term Memory (LSTM) method has been utilized. In particular, LSTM neural networks [27] are a subclass of recurrent neural networks with learning capabilities across time employing feedback connections. This technique develops short-term memory and gathers data from it by utilizing cyclic links on their hidden layer and collect information from time series and sequences. A memory cell and the three major gates of input forget and output make up every LSTM unit. By utilizing this framework, the LSTM choose which information needs to be "forgotten" and which needs to be "remembered," creating a controlled data flow and learning for the long term dependencies. Eq. (19) predicts the performance operation of LSTM unit. The layers of the developed method are shown in Fig. 2.

$$a_u = \sigma(P_u m_s + R_u n_{s-1} + t_u) \quad (19)$$

Where *R* and *P* are weight matrices, m_s represents the input, σ is the sigmoid function, and *t* is the bias term vector.

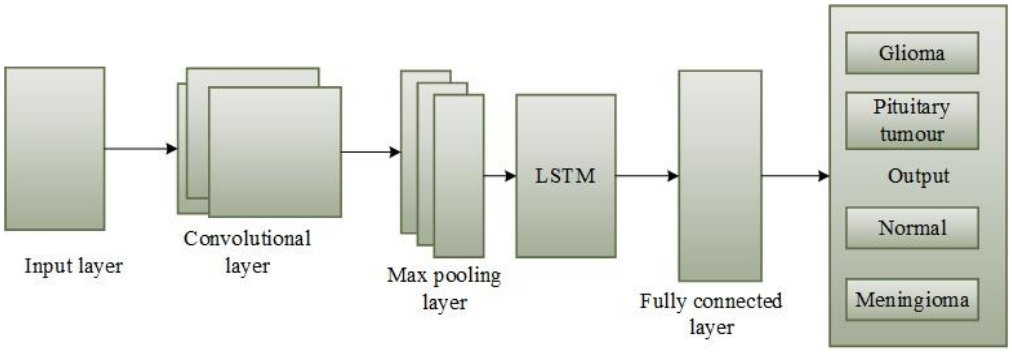

Fig. 2. Layers of the developed CNN and LSTM model.

d) Output layer: The output layer also known as fully connected layer is the completely linked layer's neurons rely on all regions of the brain's prior layer. In this layer, data is transformed into a 1-D matrix beneath the layer. There may be variations in each model's overall amount of fully connected layers. Eq. (20) is employed for feed forward in this layer.

$$a_m^s = \sum_n u_f^{s-1} v_n^{s-1} \quad (20)$$

Where *s* is the number of layer, v_n^s is the value in the created output layer, *m* and *n* is the number of neuron, u_f^{s-1} is the hidden layer weight, v_n^{s-1} is the input neuron input and a_m^s is the value of the activation function in the output layer.

The brain tumours have been correctly classified based on MRI images. Pituitary tumour, glioma, normal brain and meningioma have been discovered. The CNN-LSTM framework utilizes Bat and Grey Wolf Optimization (BGWO) algorithm for extracting the features and the overall process BGWO-CNN-LSTM is shown in Algorithm 1 and Fig. 3.

Algorithm 1: *BGWO-CNN-LSTM mechanism*

Input: *Magnetic Resonance Images*
Output: *Pituitary, Meningioma, Glioma, and Normal*
Import input image data
Let I be the input data that is taken for analysis
$I = \{I_1, I_2, I_3 \ldots.\}$
Pre-processing of images *//Gabor filter*
Segmentation of images *//Otsu thresholding*
Feature extraction *//Bat Grey Wolf Optimization*
Initialize the bat's population randomly
while (s'< Maximum number of iterations)
Adjust frequency and generate new position
Update velocity and position using eqn. (14)
else go to next step
if (random > P_m)
Select an image randomly among the best positions
Calculate local position among the selected best position
Else
calculate the global best position
Calculate the fitness of every search agent
Update local and global best positions
$s' = s' + 1$
end if
Classification *//CNN-LSTM classifier*
Classifying as Pituitary, Meningioma, Glioma, and Normal
end if
end while
end

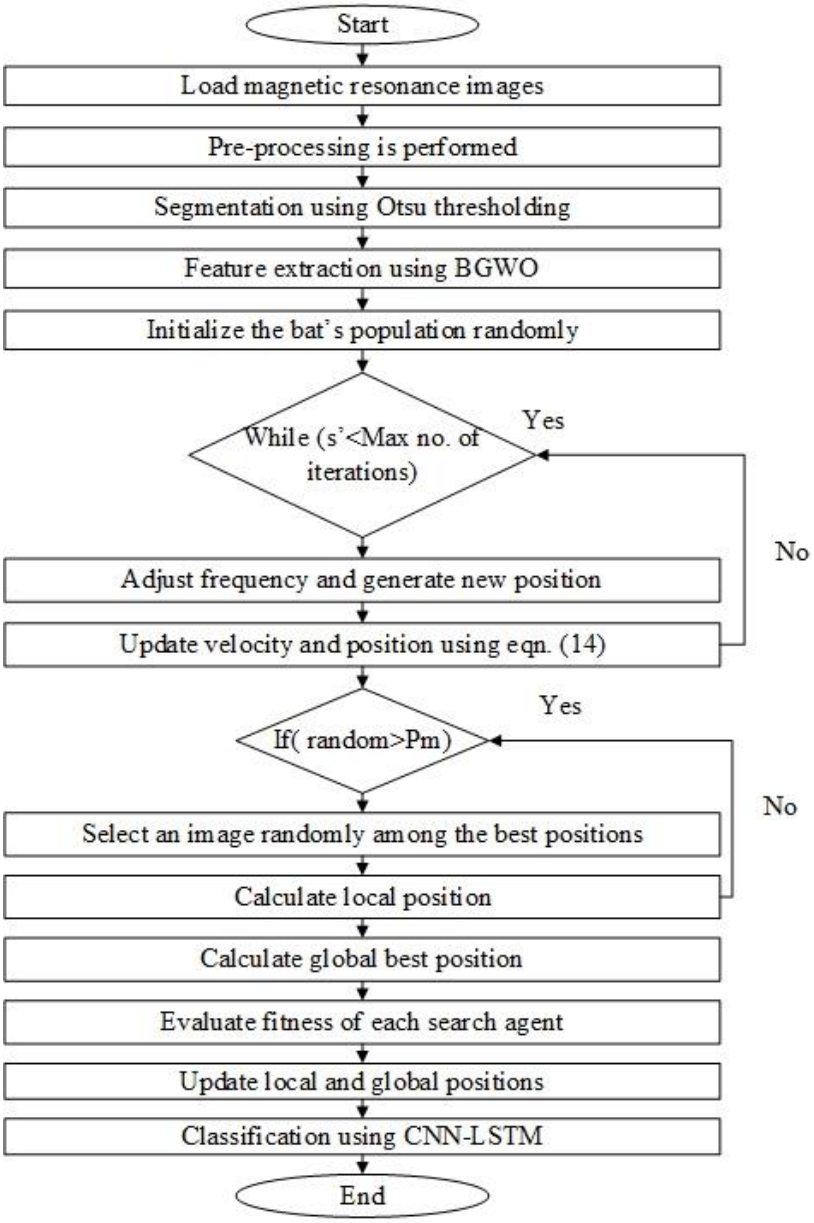

Fig. 3. BGWO-CNN-LSTM workflow diagram.

IV. RESULTS

The developed method is examined using MRI dataset. Using the Gabor filter, 6100 MRI scans of brain tumours were gathered and pre-processed. The tumours in the images are so severe. So, it is impossible for the average person to quickly spot them. Pre-processing MR images is crucial for improving the vision impact of the image before processing. Typically, the dataset's gathered images are of bad quality and the noise should be filtered out and the image is sharpened. Gabor filter is utilised as a pre-processing step. Following that many traits are initially implicitly collected. With the aid of an enhanced Otsu thresholding method, the tumour is then identified. After that, the feature extraction method utilizes the bat and grey wolf algorithm. Subsequently CNN-LSTM is utilised for classification. The proposed model achieves performance matrices of recall, accuracy, and specificity. 4100 images of brain tumours and 2000 photos of tissue are found by extracting and segmenting image features. Utilizing efficient spot images, training and testing dataset is produced. The proposed model's effectiveness is shown, and it achieves the best levels of recall, specificity, and accuracy in the identification of brain tumours. In every MRI imaging of a brain tumour, there is an error rate based on abnormal tissue. Depending on the true negative, true positive, false positive and false negative values, these can be quantified. The recall, accuracy and specificity of the technique have been evaluated on all of the images in the dataset for this research.

A. Accuracy

One of the frequently employed metrics for classification techniques is accuracy. It indicates the proportion of accurate estimates of overall predictions. The evaluation of actual

classification is known as accuracy. According to image analysis, the accuracy is a per cent that represents the total amount of pixels that have been correctly classified in relation to the total amount of pixels in the image. It assesses every single correctly placed pixel in an image. Accuracy is expressed in Eq. (21).

$$Accuracy = \frac{True_{pos}+True_{neg}}{True_{pos}+True_{neg}+False_{pos}+False_{neg}} \quad (21)$$

B. Specificity

The quantity of precisely determined true negatives is measured by specificity. Using Eq. (22), the specificity value is calculated as,

$$Specificity = \frac{True_{neg}}{True_{neg}+False_{pos}} \quad (22)$$

C. Recall

Recall is the ratio of true positives and false negatives to correct positive forecasts. The percentage of forecasts that have been appropriately identified as tumour is expressed. Eq. (23) is employed to represent recall.

$$Recall = \frac{True_{pos}}{True_{pos}+False_{neg}} \quad (23)$$

TABLE II. PERFORMANCE MATRIX COMPARISON ON THE BASIS OF ACCURACY, SPECIFICITY AND RECALL

Method	EKF-SVM	Genetic Algorithm	ANN	Proposed BGWO-CNN-LSTM
Accuracy	98.02%	92.03%	92.14%	99.74%
Specificity	94.15%	91.42%	94%	99.54%
Recall	96.44%	92.36%	89%	99.23%

The test results of the BGWO-CNN-LSTM classifier with those of other classifier methods including Extended Kalman filter with Support Vector Machine (EKF-SVM) [28], Genetic algorithm [21], Artificial Neural Networks (ANN) [20] based on the statistical characteristics of recall, accuracy and specificity is illustrated in Table II. On the basis of disease categories such as glioma, pituitary tumour, meningioma and normal, the findings are compared. 80% of image dataset are employed for training and 20% of images are employed for testing the data. The performance matrix of the suggested approach's recall, specificity and accuracy were found to be 99.23%, 99.54% and 99.74% which is higher than the existing approaches of EKF-SVM, Genetic algorithm and ANN is illustrated in Fig. 4.

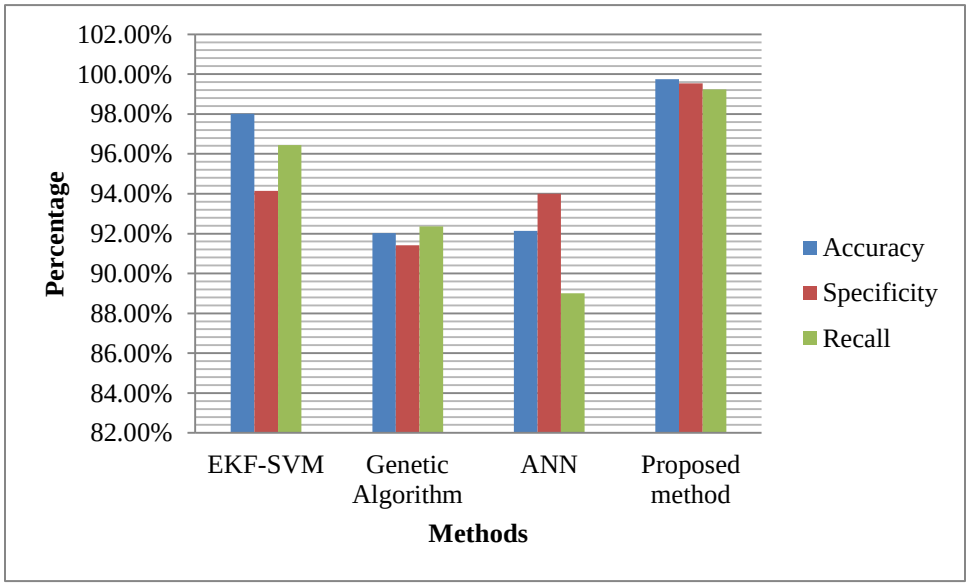

Fig. 4. Performance comparison of the developed and existing models.

V. DISCUSSION

The brain MRI dataset was used in this research work to apply a combined mechanism to recognize and classify the tumor on the images. The created method uses supervised hybrid CNN and LSTM algorithms and is intended to discriminate between normal and pathological tumors in brain pictures. Brain tumour detection techniques including Extended Kalman filter with Support Vector Machine, Genetic algorithm and ANN are trained and evaluated in order to compare their characteristics with those of traditional networks. The findings demonstrate that the suggested BGWO-CNN-LSTM model, out of these four strategies, produces greater specificity, accuracy and recall as shown in Fig. 4. A degree of recall, specificity and accuracy of 99.23%, 99.54% and 99.74% are attained using the BGWO-CNN-LSTM method. The comparison demonstrates that the suggested approach outperformed the alternatives. The suggested approach demonstrates that the BGWO-CNN-LSTM is the better approach for the recognition and classification of a brain tumour.

VI. CONCLUSION

One of the serious disorders is brain tumour identification and classification due to aberrant cell proliferation or portable spread across the body. This research work has applied a combined mechanism on brain MRI images to identify and categorise the tumour utilising the MRI dataset. Employing supervised hybrid CNN and LSTM approaches, the developed

method is designed to distinguish among normal and abnormal tumours in brain images. The input images have undergone the main pre-processing processes of normalisation, as well as the extraction of major characteristics from the pre-processed image using the Gabor filter and threshold-based segmentation approach called Otsu thresholding. To categorize brain MRI images, hybrid CNN and LSTM algorithms are applied to the labelled segmented features. It is utilized to categorize the tumours such as pituitary tumour, glioma, meningioma and normal brain. Finally, the proposed approach achieved 99.74% accuracy, 99.23% recall and 99.54% specificity. Comparison of supervised and unsupervised learning in recent technologies verifies that the suggested BGWO-CNN-LSTM method works better than other well-known CNN-based architectures for classifying the tumours. Further research could improve feature extraction algorithms by incorporating additional texture and form features and employing big datasets.

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