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S. KUMAR, U. PILANIA, N. NANDAL

A SYSTEMATIC STUDY OF ARTIFICIAL INTELLIGENCE-BASED METHODS FOR DETECTING BRAIN TUMORS

Kumar S., Pilania U., Nandal N. **A Systematic Study of Artificial Intelligence-Based Methods for Detecting Brain Tumors.**

Abstract. The brain is regarded as one of the most effective body-controlling organs. The development of technology has enabled the early and accurate detection of brain tumors, which makes a significant difference in their treatment. The adoption of AI has grown substantially in the arena of neurology. This systematic review compares recent Deep Learning (DL), Machine Learning (ML), and hybrid methods for detecting brain cancers. This article evaluates 36 recent articles on these techniques, considering datasets, methodology, tools used, merits, and limitations. The articles contain comprehensible graphs and tables. The detection of brain tumors relies heavily on ML techniques such as Support Vector Machines (SVM) and Fuzzy C-Means (FCM). Recurrent Convolutional Neural Networks (RCNN), DenseNet, Convolutional Neural Networks (CNN), ResNet, and Deep Neural Networks (DNN) are DL techniques used to detect brain tumors more efficiently. DL and ML techniques are merged to develop hybrid techniques. In addition, a summary of the various image processing steps is provided. The systematic review identifies outstanding issues and future goals for DL and ML-based techniques for detecting brain tumors. Through a systematic review, the most effective method for detecting brain tumors can be identified and utilized for improvement.

Keywords: image processing, machine learning, deep learning, hybrid techniques.

1. Introduction. The human body contains numerous organ types. The brain is one of the human body's most delicate and specialised organs. Owing to the rapid development of image-processing technology, brain tumors and their investigation are of greater interest [1]. Human brain tumors are considered harmful health conditions. An unusual tissue development in the brain or nearby areas is called a brain tumor (an intracranial neoplasm) [2]. Fundamental or metastatic brain cancers are distinguished [3]. Brain cells are the source of initial tumors, whereas cancer cells from other body components have metastasised to the brain to cause metastatic tumors [4]. Most scientists are motivated by gliomas, among the essential categories of brain cancers. The term "glioma" refers to a variety of tumors, ranging in grade from low-grade (LG) to high-grade (HG) [5]. The HG tumors are called glioblastoma multiforme (GBM), whereas LG tumors are said to be astrocytomas or oligodendrogliomas [6]. It is possible to determine if a brain tumor is benign (non-cancerous) or malignant (cancerous) [7]. Secondary and primary tumors are two different types of malignant tumors that may be distinguished [8]. A malignant tumor is more harmful than a benign one [9]. A malignant tumor can make a patient worse, even to death, by quickly entering other tissues of the brain [10].

Diagnosing brain tumors is challenging according to the brain's complex anatomy [11]. Brain tumor identification is quite complex because of the appearance, location, shape, and diverse size of tumors in the brain [12]. Detection of a brain tumor is a highly complex process at the initial stage because it cannot determine the accurate mensuration of the tumor [13]. If the tumor in the brain gets determined, proper treatment can be started to cure the harmful disease [14]. Only the form of cancer determines the course of treatment for brain tumors, including radiotherapy, chemotherapy, and surgery [15].

Medical imaging is a powerful tool for identifying non-invasive possibilities [16]. X-ray, positron emission tomography (PET), Computed tomography (CT) scan, Magnetic resonance imaging (MRI), single photon emission computed tomography (SPECT), and ultrasound are examples of non-invasive medical imaging techniques [17]. These imaging processes help identify various diseases. Using safe radio waves and magnetic fields makes MR images more accepted in successfully detecting and treating brain tumors [18]. Compared to CT, MRI produces more accurate results in medical diagnosis systems (MDS) because it offers better contrast and clarity for the body's diverse soft tissues [19].

MRI plays a powerful tool in detecting brain tumors [20]. MRI uses practical magnetic field components to identify radio frequency pulses and generate detailed organ images, bone, other internal structures, and soft tissues of the physical body. Brain tumor identification can also be made via MRI images [21]. In image processing, image improvement tools are utilised to enhance the standard of images [22]. The contrast adjustment and threshold techniques are utilised to highlight the characteristics of MRI images [23]. The histogram, edge detection, morphological, and operations segmentation are mainly used in classifying and determining the brain tumor [24].

1.1. Key contributions. Brain tumor imaging is a commendable and challenging effort in the medical field. Early brain tumor detection and localisation can save lives and give doctors more treatment options. Thus, we systematically reviewed ML and DL brain tumor recognition approaches due to their importance and benefits. The following are the main results of the literature review:

– The systematic review on brain tumor detection using image processing methods inspires researchers to create new systems using ML and DL algorithms. In other systematic review papers, they used old brain tumor detection research. The proposed systematic review briefly discusses ML and DL-based brain tumor detection methods with understandable tabulation. The systematic review uses research papers from 2020 to 2022.

– The proposed systematic review seeks to learn more about recently proposed brain tumor detection research that has not yet been reviewed. The proposed systematic review summarises ML and DL brain tumor detection methods.

– Few review papers discuss developing a brain tumor detection system using multiple methods. The proposed systematic review collected all recent research papers on ML and DL-based brain tumor detection systems to generate medical invention ideas.

A quick overview of brain tumors, imaging techniques, and different types of brain tumors sets the stage for the proposed systematic review. The systematic review is then divided into subsequent units. Section 2 consists of the review procedure, and Section 3 includes the stages used in detecting brain tumors using image processing methods. Section 4 contains ML-based brain tumor detection, Section 5 contains DL-based brain tumor detection, and Section 6 contains open challenges and research directions. Section 7 discusses the systematic review's overall conclusion and future work.

2. Stages used in detecting brain tumors using Image Processing techniques. Four processes comprise a primary method for image processing, preprocessing, extraction of features and selecting segmentation, and classification [25]. Figure 1 lists the phases employed in the image processing method for tumor detection. Initially, the input image is preprocessed using some filtering technique [26].

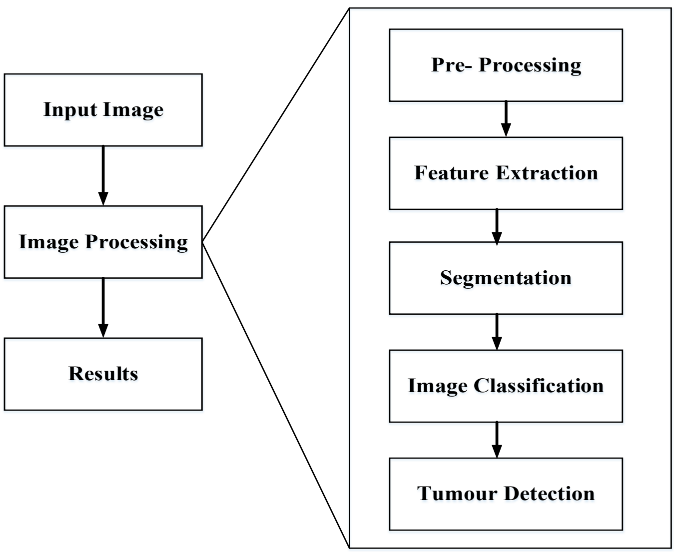

Fig. 1. Image Processing steps for brain tumor detection

After the preprocessing stage, using an effective feature extraction technique, the essential and informative features are derived [27]. The most significant and optimal characteristics are selected from the retrieved features using a feature selection method [28]. A segmentation technique is employed with an attribute extraction method to get the segmented region from the image [29]. Finally, a classifier is included for MRI image classification and to specify the kind of tumor [30].

2.1. Preprocessing. Various preprocessing techniques include fixed, adaptive, linear, non-linear, and pixel-based for different conditions [31]. These techniques are employed by considering two main aims. The primary goal is to improve the quality of images that a human observer can use. The second aim is to use the images for different processes with other algorithms to get accurate solutions [32]. The first aim includes contrast improvement, sharpening details in an image, and noise removal. The second aim examples include object segmentation and edge detection. The bias field is vital while segmenting MR images [33]. This bias field is due to the radio frequency coil imperfections known as intensity non-uniformity. The bias field can be corrected by calculating and vanishing from the collected image [34].

Different kinds of noise corrupt a medical image. Speckle, salt and pepper, and Gaussian noise can taint medical imaging [35]. It is impossible to recover essential image features when this noise is found in clinical photos. However, numerous authors use various filtering techniques to eliminate image noise. Rather than using a linear filtering technique to remove noise from an image containing edges, the median filtering technique is employed [36]. The median filter is more effective than the mean filter at preserving the image's most prominent and influential features, but it is costly and challenging to compute [37]. It is also a slow process, even when processed with fast algorithms, such as quick sort, because it must arrange all nearby values into numerical order [38]. Wiener filtering technique is flexible in the case of an image with local and spatial variable information [39]. It integrates two high and low filters and aspects managing their respective weights. This type of filter is mainly applied to CT and MR images.

Non-linear image resolution enhancement is utilised in mammographic images, but resolution and edge enhancement are coupled with noise amplification [40]. Therefore, a wavelet architecture is implemented for contrast enhancement and noise reduction. There are hybrid filters that combine wavelet transforms with an adaptive multistage non-linear filter [41]. By minimising the intensity difference between a pixel and its adjacent pixel, the mean filtering approach minimises image noise and is easier to implement [42]. The image is primarily smoothed using the filtering process. Figure 2 depicts various filters to remove noise from an input image.

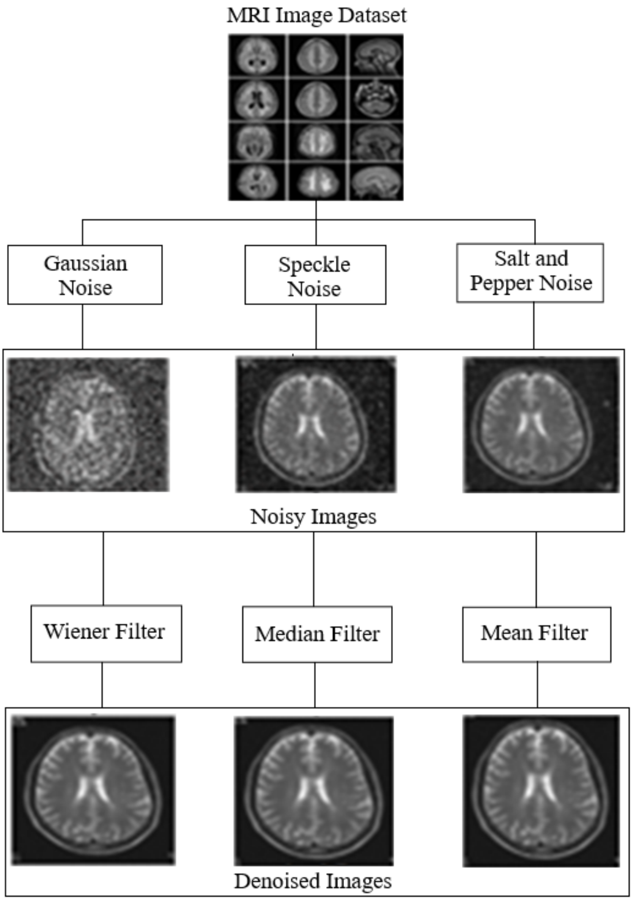

Fig. 2. Preprocessing techniques

2.2. Feature Extraction and Selection. Due to its accuracy in identifying and classifying brain tumors, feature extraction has become more critical in the medical field [43]. In the image processing system, feature extraction follows preprocessing. Feature extraction is the shape information of a structure in a pattern to simplify classification [44]. In image processing, feature extraction reduces image dimensions. The most crucial information is extracted from real photos using feature extraction algorithms, which are then shown in a two-dimensional space [45]. Every image contains tumor classification and detection features.

Various authors have developed a variety of feature extraction techniques. Some of the basic feature extraction methods include the histogram of oriented gradients (HOG), the grey level co-occurrence matrix (GLCM), the speeded-up robust feature (SURF), and the local binary pattern (LBP). For extracting features, several researchers might need hybrid strategies that make the training process more challenging. In this case, the method for choosing essential qualities is crucial. The primary function of a feature selection technique is to choose the necessary tumor identification features. The technique aims to utilise only the necessary features by eliminating superfluous ones. Numerous techniques are proposed for selecting features, including the wrapper method, principal component analysis (PCA), and PSO. Figure 3 shows various feature extraction and selection techniques.

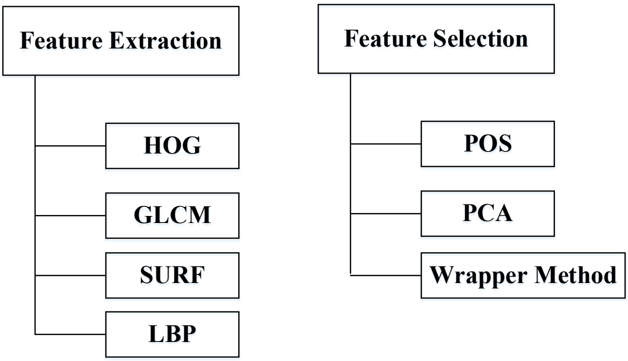

Fig. 3. Feature Extraction and Selection techniques

2.3. Image segmentation. *Segmenting an image involves breaking it into* pieces depending on different and related traits. Using the segmentation techniques, the tumor is segmented during tumor segmentation. Some segmentation techniques include edge-based, threshold, cluster-based, and region-based techniques [46, 47].

2.4. Classification. After segmentation, the medical image is classified as abnormal or usual [48]. Additionally, it is utilised to classify tumor types. SVM and CNN are examples of classification techniques [49]. Figure 4 illustrates the classification techniques utilised. Here, two main groups of brain tumors are termed primary and metastatic. Primary brain tumors originate from the brain's tissues or immediate surroundings.

Primary tumors are categorised as glial (composed of glial cells) or non-glial (developed on or in the brain's structures, including nerves, blood vessels and glands) and benign or malignant.

Metastatic brain tumors include tumors that arise elsewhere in the body. Metastatic tumors are considered cancer and malignant. The classes of malignant brain tumors are Meningiomas, Glioma, Pituitary tumors, and Pediatric brain tumors.

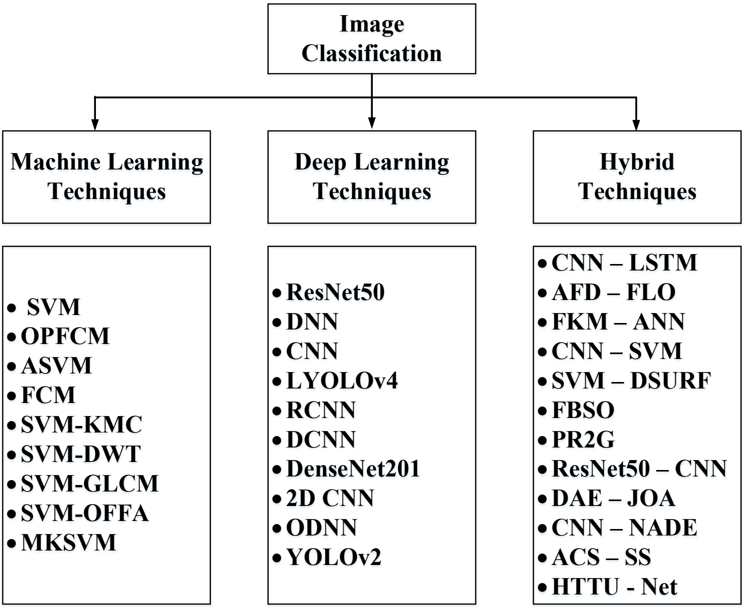

Fig. 4. Image classification

2.5. Tumor detection. The final step of an image processing technique is tumor detection. In this stage, the output image is used to make the final diagnosis of whether or not the patient has a brain tumor. It also provides information regarding the tumor's size and type [50]. The physician will then administer appropriate treatment to safeguard the patient. As a result, by identifying brain tumors at an initial point, the brain tumor detection method significantly aids patients [51].

3. Detection of brain tumors using Ml techniques. ML solves complex medical problems with high specificity and accuracy. Brain tumor detection systems use ML. The system's success is based on its effective classification strategy for medical image normality and abnormality. Many authors have detected brain tumors using ML methods. Figure 4 shows the different ML techniques to detect brain tumors.

In study [52] the authors proposed ML-based brain tumor detection and segmentation. A novel improved Kalman filter (EKF) with SVM predicts brain tumors in a five-step process. First, a non-local mean filter removed noise, and enhanced dynamic histogram equalisation brightened the image. Second, GLCM extracts features. Third, the SVM classifies extracted features. Cross-validation determines classifier efficiency in the fourth step. Finally, KMC segmentation and regional growth detect brain tumors. The dataset was 120 patients from Tiantan Hospital. The method has 98.02% accuracy, 95.39% specificity, and 97.04% sensitivity.

Study [53] proposed an optimal possibilistic FCM (OPFCM) procedure & adaptive k-nearest neighbour (AKNN) classifier to predict MRI brain tumors. Median filter denoising. The preprocessed images are given input to the extraction phase to extract the texture features. AKNN classifies extracted features. Centroid optimisation uses a competitive binary swarm optimiser (BCSO). Finally, OPFCM is used for tumor segmentation. The model was created using the BRATS dataset and achieves 99.9% accuracy.

In paper [54] the authors suggested MRG and ASVM for MRI brain tumor classification and prediction in which Manual skull stripping extracts the ROI. Median filtering denoises the image and MRG-segmented tumors. GLCM was used to extract features. ASVM is then used to classify tumors from BRATS 2015 dataset. The method has 95.83% accuracy and 91.66% sensitivity.

Study [55] suggested segmenting MRI brain tumors with FCM-rotated triangular sections. Morphological reconstruction involves erosion and dilation. After background removal, expansion, and radius contraction select the FCM optimisation area. The two processes chose the area's maximum radius and centroid from the eliminated background and used 233 patient MRIs to train the model. The method has 65.6% sensitivity, 72.6% specificity, and 90.57% accuracy.

According to paper [56] the authors proposed a DWT-SVM enhanced classification network model to detect brain tumors. Skull detection and preprocessing determine component boundaries which identify image edges. K-means clustering is used for segmentation. SVM was used for classification, while DWT and GLCM were employed to extract features. Performance metrics confirmed precision, recall, and processing time.

In study [57] the authors presented KMC & SVM classifiers to identify and classify brain tumors. The brain tumors are mainly segmented using K-means clustering. Imadjust adjusts image intensity. Pixels below a threshold are removed. DWT is used to extract image features. Finally, SVM classifies tumors from 40 benign and malignant MR image datasets. The method suggested achieves 93% classification accuracy and 99.7% segmentation accuracy.

A GLCM-based SVM classifier and semantic segmentation of brain malignancies from MRI images were suggested by the authors [58], in which Median filtering and skull stripping are used in the preprocessing stage. Then, watershed thresholding is used for segmentation. To measure the correlation, contrast, homogeneity, and energy, GLCM has been used. SVM is used to classify images. Kaggle and Figshare datasets trained the model. The method detects brain tumors with 93.05% accuracy.

MRI brain tumor segmentation utilising the improved Gabor wavelet transform (IGWT) and rough KMC was suggested by paper [59]. IGWT changes the domain by replacing the image. GLCM extracts and oppositional fruit fly algorithm (OFFA) optimise the features. SVM was used as a classifier. K-means is used to segment abnormal images. BRATS 2018 was used to train the model. The method achieves 99.79% accuracy, 97.27% sensitivity, and 99.92% specificity.

According to paper [60] the authors proposed SVM-based brain tumor classification. The scheme uses Kaggle data. Median filter preprocessing is used to improve image quality. GLCM is used to extract image features. From the GLCM texture, the following properties are extracted: contrast, correlation, energy, homogeneity, entropy, autocorrelation, cluster prominence, cluster shade, difference entropy, difference variance, and dissimilarity. After that, SVM classifies brain tumor images. The method detects brain tumors with 93.33% accuracy.

Study [61] used rough k-means and multi-kernel SVM in MRI images to efficiently classify and segment brain tumors. IGWT is used to extract features, and OFFA is used to select optimised features. As a classifier, Multi-kernel SVM (MKSVM) is employed. Modified rough KMC (MKMC) is applied to segment the tumor image. The method has 99.72% accuracy, 99.72% specificity, and 99.71% sensitivity.

Using DWT & SVM, paper [62] enhanced the extraction of features and forecast of brain tumors. Denoising is done during preprocessing. To recover picture characteristics, DWT and GLCM are employed. The Kaggle dataset was employed to train the SVM model, which is employed to classify data. The method achieves 98.97% accuracy and 98.87% precision.

Brain tumor identification based on SVM was suggested by the authors [63] by using collected data. Preprocessing, classification, segmentation, and brain tumor detection are performed on the input image.

SVM is used for classification. The method has 98% sensitivity, 98.30% accuracy, and 100% specificity.

Table 1 lists ML brain tumor detection methods, tools, pros, cons, and parameters.

Table 1. Detection of brain tumor using Machine Learning techniques

Reference No	Author And Year	Method used	Dataset used	Tool used for implementation	Advantage	Disadvantage	Parameters analysed
[52]	Chen et al. [2021]	SVM EKF GLCM	Tiantan Hospital 120 patients information	–	The computational complexity is due to the use of standardisation in input images	The segmentation results are insufficient to predict the brain tumor	Accuracy – 95.39% Sensitivity – 97.04 % Specificity – 95.39%
[53]	Kumar et al. [2021]	OPFCM AKNN BCSO	BRATS MICCAI	Matlab 2014a	Centroid optimisation is done to enhance system performance	Classification accuracy is significantly less	Accuracy – 99.9%
[54]	Reddy et al. [2021]	MRG ASVM GOA	BRATS 2015	Matlab	Less dependence on operator expertise	More computational time to predict tumor	Accuracy – 95.83% Sensitivity – 91.66%
[55]	Sheela et al. [2021]	FCM	MRI images	–	The approach limits the availability of MRI images	The proposed method's accuracy wasn't tested.	Accuracy – 90.57% Dice-score Sensitivity – 65.6% Specificity – 72.6%
[56]	Gokula-lakshmi et al. [2020]	SVM DWT GLCM	DICOM	Matlab	Simple to understand and implement	The results will not always be more accurate	Precision - 96.7 Recall – 95.4 Processing time – 74.5s

Continuation of Table 1

[57]	Chander et al. [2020]	KMC SVM	MRI images	–	The image's undesirable pixels are eliminated to prepare it for processing	Ineffective method for brain tumor detection	Accuracy – 99.7%
[58]	Hussain et al. [2020]	SVM GLCM	Kaggle Figshare	Matlab	Watershed segmentation is used that selects the best seed region for accurate segmentation of the tumor region	Noise may lead to the undesired final result	Accuracy – 93.05%
[59]	Kumar et al. [2020]	SVM OFFA IGWT	BRATS 2018	Matlab	The technique needs only a least human interaction	The method does not apply to images with various foreground and background artefacts	Accuracy – 99.79% Sensitivity – 97.27% Specificity – 99.92%
[60]	Shahajad et al. [2020]	SVM GLCM	Kaggle	Matlab	A compelling feature extraction technique is used	Computationall y expensive	Accuracy – 93.05% Sensitivity – 98%
[61]	Krishna-kumar et al. [2020]	MKSVM MKMC OFFA		–	Simple and computationall y fast	The method is not eligible to segment the tumor part more accurately	Accuracy – 99.72% Specificity – 99.72% Sensitivity – 99.71%
[62]	Mehrotra et al. [2020]	SVM GLCM DWT	Kaggle	Matlab R2018a	Optimised features are extracted using two techniques	Difficult to extract the border or edge features	Accuracy – 98.97% Precision – 98.87%
[63]	Sarkar et al. [2020]	SVM	MRI images	Matlab	Simple to understand	Inefficient technique to detect brain tumors	Accuracy – 98.3% Sensitivity – 98% Specificity – 100%

4. Brain tumor detection using Dl techniques. To utilise the data for pattern & image recognition, language translation, voice recognition, and decision-making, DL tries to replicate the human brain. Additionally, it is considered a subset of ML. It learns on its own from the data it is given. In practice, the technique is widely employed for a variety of purposes. The technology is utilised to identify brain cancers, among its most important medical uses. Various DL classifiers with low error potential detect abnormalities in medical images. Numerous authors have proposed various DL techniques for diagnosing brain tumors to achieve the best accuracy. Figure 4 shows the different DL techniques to detect brain tumors.

Paper [64] recommended transfer learning and data augmentation to identify brain cancers in MRI images. PCA-based data augmentation is used to reduce the dataset dimensions. Transfer learning is utilised to initialise model weights without training random distributions. Cross-entropy is used to evaluate loss function. The data augmentation technique is validated by training a network known as ResNet50. The cancer genome atlas low-grade glioma (TCGA-LGG) dataset was utilised for training the model. Python-based TensorFlow and Keras libraries are used to model the network. Colab implemented the prosed model. The proposed strategy achieved better accuracy, specificity, sensitivity, and 92.34% of the F1 score.

A DL approach for MRI brain tumor identification was put forth by the authors [65]. A three-step preprocessing is performed on the input image to boost the contrast, lengthen the histogram, and enhance the clarity of MRI pictures. A preprocessing blind referenceless image spatial quality evaluator (BRISQUE) is used to verify the output image's quality. DNN is used as a brain tumor classifier. Batch normalisation is used to speed up model training. The model was trained using the Navoneel brain tumor and Sartaj brain MRI datasets. Keras and Python libraries are used to model the network, which was implemented on Colab. The strategy had 98.22% accuracy, 96.12% sensitivity, 99.65% specificity, and 97.85% F1 score.

In paper [66] the authors proposed CNN-based brain tumor detection. The approach has three steps: augmentation, preprocessing, and classification. The proposed work enlarges a small dataset using augmentation. The RGB image is transformed to grayscale, cropped, low pass filtered, and binary converted during image preprocessing. CNN is used to categorise and identify different kinds of brain tumors. The dataset includes 2065 augmented brain MRI images. The model has an 89.16% F1 score, 87.42% accuracy, and 33.25% relative loss.

For the identification and segmentation of brain tumors, study [67] presented a multi-task network. The suggested technique located the brain tumor and its mask. A contextual brain tumor selection network identified brain tumors, and a 3D atrous residual network determined the mask. BRATS2015, 2017, and 2018 datasets were used to train the network. The strategy achieves an 81.41% dice score and 92.0% sensitivity.

Brain tumor diagnosis using neural network-based end-to-end predictive intelligence was proposed by study [68]. It was easier to forecast brain cancers using LYOLOv4-RNN. The suggested model was trained using brain tumor data from Kaggle. The suggested technique had a 97% accuracy rate for detecting brain cancers.

A recurrent convolutional neural network (RCNN)-based neural net for brain tumor detection and classifying was proposed by paper [69]. A simple framework for analysing brain tumors is suggested to shorten the architecture's completion time. Two CNN channels are utilised initially with a low complex framework for classification, and a similar structure is used as an extractor in RCNN for brain tumor deduction. The model was trained using datasets from Figshare and Kaggle 2020. The design has 98.21% accuracy and 98.83% confidence.

In study [70] the authors proposed DL-based 2D MRI brain tumor detection. DNN is used to segment 2D brain tumors. The Znet-based approach uses skip connection, data amplification, and encoder-decoder frameworks. Data augmentation is performed using an open-source and free Python library, Albumentation. ADAM optimiser is used to train the model. The model was built using the Cancer Genome Atlas Low-Grade Glioma (TCGA-LGG) dataset. The proposed method achieves 99.6% accuracy and 81% F1-score.

To identify and categorise brain cancers in enhanced MRI images, the authors [71] suggested an enhanced DCNN framework & optimisation technique. The suggested approach uses DCNN with enhanced Harris Hawks Optimization (HHO). HHO and grey wolf optimisation (GWO) were combined to boost efficiency. Tumors are divided using Otsu thresholding. The classifier was tested using data on brain tumors from Kaggle. 97% accuracy, 99% precision, 95% recall, and 97% f-measure are attained by the suggested strategy.

A DL-based decision-support system for multi-model brain tumor identification was proposed by the authors [72]. Deep transfer learning is used to train the Densenet201 DL model, which has been fine-tuned. The modified genetic algorithm (MGA) and entropy-kurtosis-based high feature values (EKbBHFV) are used to choose the best features. The selected characteristics are combined via a non-redundant serial-based method, and then a multi-class SVM classifier is used to categorise them. The model was trained using BRATS 2018 and 2019. The method had a 99.3% F1 score, 99.7% accuracy, and 99.8% precision.

DL network-based computer-aided brain tumor identification from MRI images was proposed by the authors [73]. The suggested method divides brain cancers into two categories: tumor and normal, by using a 2D CNN. The input image is improved with filters, cropped, rotated, and scaled in preprocessing. The ReLU function is thus made available to enhance non-linearity. Every feature map has a pooling layer added to it. The wholly connected neural network receives these features for categorisation. The proposed method has 97% accuracy, 97% F1 score, 94% recall, and 100% precision.

Brain tumor detection utilising in-depth features and SVM focusing on data-restricted technique was proposed by the authors [74]. The proposed method uses VGG16, AlexNet, and VGG19 pre-trained networks. A deep fusion approach was used to improve classification accuracy. Models were trained on BRATS and TCIA datasets. The proposed method achieves 97.89% accuracy and a 97.92% F1 score.

Brain tumor diagnosis from PET and MRI images using wavelet-based image fusion was suggested by the authors [75]. The input image is fused using DWT and several cutting-edge fusion rules. Next, a GLCM extracts features. An optimized DNN (ODNN) then classifies images as normal or abnormal. Spider monkey optimization (SMO) optimises network weight. After categorisation, weighted k-means extract the tumor from the abnormal image. The model was trained on BRATS. The method has 89% sensitivity, 93% specificity, and 93% accuracy.

Using YOLOv2 and CNN, study [76] suggested MRI brain tumor detection. The input image is denoised by homomorphic wavelet filters. The pre-trained Inceptionv3 model is employed to extract features. Then feature selection is made using the non-dominated sorted genetic algorithm (NSGA). To categorise the chosen traits, YOLOv2 is utilised. McCulloch's Kapur entropy then segments the tumor from classified images. The model was trained on BRATS 2018, 2019, and 2020 brain tumor datasets. The proposed method achieves 89.4% PSNR, 78.03% SNR, 36% MSE, 97% dice score, and 84% accuracy.

Table 2 shows the method, tool, advantages, disadvantages, and parameters analysed for different DL techniques for brain tumor detection.

Table 2. Brain tumor detection using deep learning

Reference No	Author and Year	Method used	Dataset used	Tool used for implementation	Advantage	Disadvantage	Parameters analysed
[64]	Isaza et al. [2022]	PCA ResNet50	TCGA-LGG	Colab	Data augmentation is utilised for training the network with small data sets	It Consumes more time to detect tumors	Specificity – 92.34% Sensitivity – 92.34% F1-score – 92.34%
[65]	Musallam et al. [2022]	DNN BRISQUE	Sartaj brain MRI Navoneel brain tumor	Colab	Normalisation technique is used to train the model fast	Brain tumor regions are not segmented	Accuracy – 98.22% Sensitivity – 96.12% Specificity – 99.65% F1-score – 97.85%
[66]	More et al. [2021]	CNN	The dataset created from augmentation	Matlab	The augmentation technique is used to generate smaller datasets	Computational cost is high	F1-score Accuracy – 87.42% Relative loss – 32.25%
[67]	Le et al. [2021]	Contextual detection network 3D atrous residual network	BRATS2015 BRATS2017 BRATS2018	Matlab	The multi-class network is framed for accurate brain tumor detection	The functionalities of prediction are insufficient	Dice score – 81.41% Sensitivity – 92.0%
[68]	Ma et al. [2021]	LYOLOv4-RNN	Kaggle brain tumor	-	A light weigh neural technique is used	The method can identify the tumor but with low accuracy	Accuracy – 97%
[69]	Kesav et al. [2021]	RCNN	Figshare Kaggle 2020	Matlab 2020	Decrease in algorithm execution time	Important features are not selected	Accuracy – 98.21% Confidence score – 98.83%
[70]	Ottom et al. [2022]	Z-net	TCGA-LGG Albumentation	-	Detected tumor at an early stage	Require more time to detect the tumor	Accuracy – 99.6% F1-score – 81%

Continuation of Table 2

[71]	Qader et al. [2022]	DCNN HHO GWO	Kaggle	Python	Optimisation algorithms are used to optimise the network	No preprocessing technique is used	Accuracy – 97% Precision – 99% Recall – 95% F-measure – 97%
[72]	Sharif et al. [2021]	Densenet201 EKbHFV MGA SVM	BRATS2018 BRATS2019	Matlab 2020	Optimised features are selected for the accurate detection of tumors	Need effective techniques to enhance the robustness of the classifier	Accuracy – 99.7% Precision – 99.8% F1-score – 99.3%
[73]	Chanu et al. [2021]	2D CNN	Brain tumor images with normal and tumor	Keras	Applicable for 2D MRI images	Cannot detect the type and size of the tumor	Accuracy – 97% F1-score – 97% Recall – 94% Precision – 100%
[74]	Sethy et al. [2021]	SVM vgg16 alexnet vgg19	BRATS TCIA	Matlab 2020	It avoids the reproduction of MR images	Delay in tumor detection due to increased noise in the images	Accuracy – 97.89% F1-score – 97.92%
[75]	Preethi et al. [2021]	ODNN SMO DWT GLCM	BRATS	Matlab	Detected the accurate size and location of the tumor	Computational complexity	Accuracy – 93% Sensitivity – 89% Specificity – 93%
[76]	Sharif et al. [2021]	YOLOv2 CNN NSGA	BRATS 2018 BRATS 2019 BRATS 2020	Matlab	An effective filtering technique is used to denoise the image	No accurate detection is provided with the proposed approach	Accuracy – 84% PSNR – 89.4% SNR – 78.03% MSE – 36% Dice score – 97%

5. Hybrid techniques for brain tumor detection. To improve the network model's detection capability, both DL and ML-based approaches are combined and renamed hybrid approaches. The hybrid approach entails integrating two or more classifiers to improve the model's accuracy and decrease its error rate. Figure 4 depicts the various hybrid methods used to detect brain tumors.

The idea of CNN and LSTM-based brain tumor identification on 3D MRI scans were first forth by the authors [77]. A temporal distribution function envelops the hybrid technique. The model was trained using BRATS 2019, 2018, and 2020. The 3D imageries are normalised and shrunk using the min-max technique to improve speed. 98.83% F1-score, 98.95% precision, 98.90% accuracy, and 98.78% recall are all achieved using the technique.

Brain tumor detection utilising hybrid DL and adaptive squirrel search optimisation was suggested by the authors [78]. Adaptive fuzzy deep learning with frog leap optimisation (AFD-FLO) algorithms was used to determine image abnormality. Error minimisation technique is used to improve the classification. The adaptive flying squirrel (AFS) algorithm segments abnormal images and then analyses tumor size to determine severity. BRATS dataset was used t train the model. The suggested technique has 0.0043 FPR, 0.543 FNR, 99.6% accuracy, 99.9% sensitivity, and 99.8% specificity.

In paper [79] the authors proposed a hybrid brain tumor segmentation method using Fuzzy K-means (FKM) and ANN algorithms. Wiener filters were used to denoise input images. GLCM then extracts features from preprocessed images. ANN is used to determine image normality. FKM is utilised to segment abnormal images. The model was trained on BRATS. The method achieves 94% accuracy, 98% sensitivity, and 99% specificity.

According to paper [80] the authors put forth a hybrid approach employing CNN and SVM for automatically categorising brain tumors. To boost performance, SVM and CNN are combined. CNN is utilised to extract features. The model was developed using Figshare MRI scans. The method has 95.82% accuracy, 97.3% precision, 98.6% recall, and 99.3% specificity.

Study [81] suggested a hybrid method to classify brain tumors. The suggested stages are intensity normalisation, extraction of features, and classification. DSURF and histogram of oriented gradients (HOG) are coupled to extract the features. The min-max approach is used to normalise the intensity of an image. DSURF extracts dense feature points, and HOG divides the image into cells. Then SVM is used to classify images. The proposed work uses Nanfang Hospital data. The proposed method achieves

90.27% accuracy, 84.89% sensitivity, 92.61% specificity, 77.55% precision, and 81.05% F1 score.

For the categorisation of MRI brain tumors, the authors [82] developed hybrid fuzzy brain-storm optimisation (FBSO). GLCM is used to extract features. The BSO prioritises the cluster centres. A fuzzy network then optimises network structure iteratively. The BRATS 2018 dataset was used to train the model. The method achieves 93.85% accuracy, 94.77% precision, 95.77% sensitivity, and a 95.42% F1 score.

A three-phase brain tumor segmentation recognition system utilising patches-based updated run length region growth was proposed by the authors [83] (PR2G). SVM classification starts the scheme. Then Infinite feature selection (IFS) extracts three optimised features. Carelieri estimator is then used to estimate the abnormal and normal tumors. The model was trained using BRATS and Whole Brain Atlas (WBA) datasets. The method had a 97% accuracy rate.

A hybrid CNN was suggested by the authors [84] to identify brain tumors. The Resnet50 basic model is used in this approach. Without altering the CNN model, this structure adds ten new layers while removing the previous five. The output of the convolutional layer is made simpler by the CNN pooling layer. The softmax layer then determines if the image is tumorous or not. The model was trained using the Kaggle brain tumor detection database. The suggested methodology achieves 100% specificity, 94.7% sensitivity, 96.90% F1 score, and 97.01% accuracy.

The categorisation of brain tumors that used a hybrid deep auto-encoder and Bayesian fuzzy clustering (BFC) segmentation was suggested by the authors [85]. A non-local mean filter removes noise from the image as input. Segmentation is accomplished using BFC. Scattering transform (ST) and wavelet packet Tsallis entropy (WPTE) retrieve robust features similar to information-theoretic measurements. Deep auto-encoder-based Java optimisation algorithm (DAE-JOA) then classifies tumor regions. BRATS 2015 dataset was used in the proposed approach. The proposed method had 98.5% accuracy, 96% sensitivity, 99.54% specificity, and 96% precision.

Brain tumor diagnosis from MRI images using a hybrid model that combines neural autoregressive distribution estimates with CNN was proposed by the authors [86]. (CNN-NADE). The dataset used contained 3064 T1-weighted CE-MR images. The proposed method achieves 95% accuracy, 94.64% sensitivity, 97.42% specificity, and 94.49% precision.

In paper [87] the authors presented the hybrid adaptive cuckoo search-squirrel search (ACS-SS) method to find brain tumors. Brain tumor images are edge-extracted using optimal multi-level thresholding.

The method of extracting features is GLCM. T2-w brain MR images were used to train the approach. SSIM, FSIM, PSNR, and computation time are used to evaluate the efficacy of the hybrid approach.

An automatic brain tumor-segmented hybrid two-track U-Net was suggested by the authors [88]. (HTTU-Net). Batch normalisation and leaky Relu activation make up the suggested architecture. Two tracks have different layers and kernel sizes. To overcome the problem of class imbalance, focal loss, loss functions, and generalised dice (GDL) are used. The model was trained on BRATS 2018. The proposed scheme had an 86.5% dice coefficient and 99.9% specificity.

Table 3 shows the method, tool, advantages, disadvantages, and parameters analysed for different hybrid techniques for brain tumor detection.

Table 3. Brain tumor detection using Hybrid techniques

Reference No	**Author and Year**	**Method used**	**Dataset used**	**Tool used for implementation**	**Advantage**	**Disadvantage**	**Parameters analysed**
[77]	Montaha et al. [2022]	CNN-LSTM	BRATS 2018 BRATS 2019 BRATS 2020	–	The images are resized to decrease computational complexity	Some enhancement is required in the network model	Accuracy – 98.9% F1-score – 98.83% Precision – 98.95% Recall – 98.78%
[78]	Deb et al. [2021]	AFD-FLO AFS	BRATS	Matlab	Error minimisation strategy is used for accurate classification	Difficult to choose fitness function	Accuracy – 99.6% Sensitivity – 99.9% Specificity – 99.8% FPR – 0.0043 FNR – 0.543
[79]	Pitchai et al. [2021]	FKM-ANN	BRATS	Matlab 2017a	The learning model is fast	Ineffective algorithm to detect brain tumors	Accuracy – 94% Sensitivity – 98% Specificity – 99%

Continuation of Table 3

[80]	Deepak et al. [2021]	CNN-SVM	Figshare	Matlab 2018a	The hybrid approach is simple and powerful	Ineffective methods to detect and segment brain tumors	Accuracy – 95.82% Precision – 97.3% Recall – 98.6% Specificity – 99.3%
[81]	Ayadi et al. [2020]	SVM DSURF-HoG	Brain tumor MRI images	–	Used hybrid technique for feature extraction	Brain tumor classification is not accurate	Specificity - 77.55% Accuracy – 90.27% Precision – 77.55% Sensitivity – 84.89% F1-score – 81.05%
[82]	Narmatha et al. [2020]	FBSO	BRATS 2018	–	The method increases the robustness of detecting brain tumors	No preprocessing is done so that the input images are too noisy to process	Accuracy – 93.85% Precision – 94.77% Sensitivity – 95.77% F1-score – 95.42%
[83]	Kalaiselvi et al. [2020]	PR2G SVM	WBA BRATS	–	For the recognition of brain tumors, an efficient hybrid method is employed	The usage of a large dataset reduces the performance of the system	Accuracy – 97%
[84]	Cinar et al. [2020]	Resnet50–CNN	Kaggle	–	Simple and powerful	An inefficient hybrid method for brain tumor detection	Accuracy – 97.01% F1-score – 96.90% Specificity – 100% Sensitivity – 96.90%
[85]	Raja et al. [2020]	DAE-JOA WPTE BFC ST	BRATS 2015	Matlab	An optimisation is utilised to minimise the complexity of the network	Significantly less exactness in detecting brain tumors	Accuracy – 98.5% Sensitivity – 96% Specificity – 99.54% Precision – 96%

Continuation of Table 3

[86]	Hashemzehi et al. [2020]	CNN-NADE	3064 T1-weighted CE-MR images	Colab	CNN integrated with NADE helps to decrease processing time	No preprocessing is done to raise the image's quality	Accuracy – 95% Sensitivity – 94.64% Specificity – 97.42% Precision – 94.49%
[87]	Agarwal et al. [2020]	ACS-SS GLCM	T_2-w brain MR images	Matlab	Optimised multi-level thresholding is done for edge information	Computationally expensive when compared to other approaches	SSIM – 96.84% FSIM – 99.21%
[88]	Nagwa et al. [2020]	HTTU-Net	BRATS 2018	Keras TensorFlow	The method overcomes the problem of class imbalance	Due to the hybridisation of two tracks, the complexity increases	Dice coefficient – 86.5% Specificity – 99.9%

6. Open challenges and research directions. It is evident from the systematic review that the authors are focusing more on DL, ML, and hybrid techniques due to their ability to detect brain tumors more precisely. Even though the computational intelligence of ML and DL systems is rising, they still deal with various issues, some of which are listed here.

Collaboration and interoperability. The authors use AI-based software and hardware to detect brain tumors. A producer's rules, interfaces, and regulations cannot match those of other producers of the same product with similar functionality. It brings up the interoperability issue. Manufacturers, scientists, and physicians must work together to improve brain tumor treatments.

Privacy & security. Medical and personal data must be secured and private. Data privacy, not security, should be addressed. Brain tumor patients have privacy rights. Medical data growth raised the issue of patient data security. Thus, authors must concentrate on creating secure and private algorithms.

Resource efficient techniques. The applications of DL and ML come with limitations in hardware. Computation processing of medical data exacerbates the issue. Eventually, more computation resources and memory are needed when the processing power increases. The input image's preprocessing is essential to image processing. Preprocessed photos take longer and take up more room, but the outcomes are much more accurate.

Nowadays, images can be processed without preprocessing or object identification. The authors can focus more on these techniques to reduce cost and overhead. Thus, DL and ML-based brain tumor identification necessitates a resource-efficiency assessment of current methods.

7. Conclusion and future work. The systematic review thoroughly summarises the methods used to identify brain cancers by DL, ML, and hybrid techniques. Recent research into detecting brain tumors has utilised DL and ML techniques in the medical domain, as highlighted by this review. Four main phases – preprocessing, feature extraction, selection, segmentation, classification, and detection – are essential to diagnose brain cancers using image processing. Authors from all over the world are actively working to improve these techniques by identifying multiple potential avenues. The most crucial element is raising the accuracy of classification. The training data must be increased to achieve this because additional data will lead to a more accurate answer. The most effective results are obtained by combining ML and DL techniques. Additionally, minuscule adjustments can sometimes result in an improvement. For instance, numerous authors omit preprocess techniques for removing image noise. While detecting brain tumors, this slight variation in the technique yields an inaccurate result. Based on the systematic review, the recognition accuracies of brain tumors vary depending on the feature extraction techniques and classifiers used in the models. This systematic review gives a succinct summary of the open research topics, which may be used to overcome the limitations of the present ML and DL-based techniques for diagnosing brain tumors. Integration of XAI strategies is necessary to improve AI systems in the medical domain. It will increase physicians' confidence in diagnosing and treating brain tumors. In addition, the quality of interoperability and training data are crucial elements in developing DL and ML-based solutions. It must address several additional concerns, such as security, privacy, and resource efficiency, to make the best DL and ML-based findings more accurate and useful. Researchers currently working in the area of medical & AI applications for ML and DL-based brain tumor diagnosis can significantly benefit from the proposed systematic review.

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Kumar Sanjeet — Assistant professor, Deen Dayal Upadhyaya College, University of Delhi. Research interests: programming language, data structures and algorithms, machine learning, deep learning.. sanjuonline1@gmail.com; Azad Hind Fauj Marg, Dwarka Sector-3, Dwarka, Delhi, 110078, New Delhi, India; office phone: +91(11)2509-9380.

Pilania Urmila — Ph.D., Dr.Sci., Associate professor, Department of computer science and technology, Manav Rachna University. Research interests: computer vision, image processing, information security. The number of publications — 22. urmilapilania01@gmail.com; Aravali Hills, Faridabad, 121004, Haryana, India; office phone: +91(129)419-8000.

Nandal Neha — Ph.D., Associate professor, Gokaraju Rangaraju Institute of Engineering and Technology. Research interests: machine learning, deep learning, pattern recognition, data mining. The number of publications — 22. nehanandal012@gmail.com; Bachupally, Nizampet Rd, Kukatpally, Telangana, 500090, Hyderabad, India; office phone: +91(720)771-4441.

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С. Кумар, У. Пилания, Н. Нандал

СИСТЕМАТИЧЕСКОЕ ИССЛЕДОВАНИЕ МЕТОДОВ ОБНАРУЖЕНИЯ ОПУХОЛЕЙ ГОЛОВНОГО МОЗГА НА ОСНОВЕ ИСКУССТВЕННОГО ИНТЕЛЛЕКТА

Кумар С., Пилания У., Нандал Н. **Систематическое исследование методов обнаружения опухолей головного мозга на основе искусственного интеллекта.**

Аннотация. Мозг считается одним из наиболее эффективных органов, контролирующих организм. Развитие технологий сделало возможным раннее и точное обнаружение опухолей головного мозга, что существенно влияет на их лечение. Применение искусственного интеллекта значительно возросло в области неврологии. В этом систематическом обзоре сравниваются последние методы глубокого обучения (DL), машинного обучения (ML) и гибридные методы для обнаружения рака мозга. Дается оценка 36 недавних статей, посвященных этим методам, с учетом наборов данных, методологии, используемых инструментов, достоинств и ограничений. Статьи содержат понятные графики и таблицы. Обнаружение опухолей головного мозга в значительной степени опирается на методы машинного обучения, такие как метод опорных векторов (SVM) и метод нечетких C-средних (FCM). Рекуррентные сверточные нейронные сети (RCNN), плотная сверточная нейронная сеть (DenseNet), сверточные нейронные сети (CNN), остаточная нейронная сеть (ResNet) и глубокие нейронные сети (DNN) — это методы DL, используемые для более эффективного обнаружения опухолей головного мозга. Методы DL и ML объединяются для разработки гибридных методов. Кроме того, приводится краткое описание различных этапов обработки изображений. Систематический обзор выявляет нерешенные проблемы и будущие цели для методов на основе DL и ML для обнаружения опухолей головного мозга. С помощью систематического обзора можно определить наиболее эффективный метод обнаружения опухолей головного мозга и использовать его для улучшения.

Ключевые слова: обработка изображений, машинное обучение, глубокое обучение, гибридные методы.

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Кумар Санджит — доцент, колледж Дин Дайал Упадхьяй, Университет Дели. Область научных интересов: язык программирования, структуры данных и алгоритмы, машинное обучение, глубокое обучение. sanjuonline1@gmail.com; Азад Хинд Фаудж Марг, сектор Дварка-3, Дварка, Дели, 110078, Нью-Дели, Индия; р.т.: +91(11)2509-9380.

Пилания Урмила — Ph.D., Dr.Sci., доцент, кафедра компьютерных наук и технологий, Университет Манав Рахна. Область научных интересов: компьютерное зрение, обработка изображений, информационная безопасность. Число научных публикаций — 22. urmilapilania01@gmail.com; Холмы Аравали, Фаридабад, 121004, Харьяна, Индия; р.т.: +91(129)419-8000.

Нандал Неха — Ph.D., доцент, Инженерно-технологический институт имени Гокараджу Рангараджу. Область научных интересов: машинное обучение, глубокое обучение, распознавание образов, интеллектуальный анализ данных. Число научных публикаций — 22. nehanandal012@gmail.com; Бачупалли, улица Низампет, Кукатпалли, Телангана, 500090, Хайдарабад, Индия; р.т.: +91(720)771-4441.