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RESEARCH ARTICLE

Neuro-VGNB: Transfer Learning-Based Approach for Detecting Brain Stroke

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ABSTRACT A brain stroke occurs when blood flow to the brain is interrupted leading to potential brain damage and loss of functions controlled by the affected area. Timely diagnosis and intervention are critical for minimizing long-term disabilities and improving recovery outcomes.This study addresses the critical challenge of brain stroke detection by utilizing a combination of deep learning and machine learning techniques. We first extracted features from the VGG16 model, a well-established convolutional neural network known for its efficacy in image classification tasks. These extracted features were then enhanced and transferred using the Gaussian Naive Bayes (GNB) model, integrated with non-negative matrix factorization to optimize feature representation. Our innovative approach, termed Neuro-VGNB, aims to leverage these advanced methodologies to improve classification accuracy significantly.To evaluate the effectiveness of our Neuro-VGNB model, we conducted comprehensive comparisons between traditional spatial features and the newly proposed transfer features. Remarkably, the Logistic Regression (LR) model yielded a high accuracy score of 99.96% indicating the robustness of our method. Furthermore, we employed k-fold cross-validation to ensure reliable performance assessment and to facilitate state-of-the-art comparisons with existing methods in the literature. The findings of this study not only highlight the potential of our Neuro-VGNB approach in enhancing the detection of brain strokes but also demonstrate its applicability in clinical settings. Our results suggest that integrating advanced deep learning techniques with machine learning can significantly improve diagnostic accuracy paving the way for more effective stroke detection systems.

INDEX TERMS Brain stroke, machine learning, transfer learning, Neuro-VGNB and VGG-16.

I. INTRODUCTION

Brain stroke also known as a cerebrovascular accident (CVA) occurs when blood flow to a part of the brain is interrupted or reduced [1] preventing brain tissue from receiving essential nutrients and oxygen. This disruption [2] can be caused by a blockage in an artery (ischemic stroke) or a burst blood vessel (hemorrhagic stroke). Without immediate medical intervention, brain cells begin to die within minutes, leading to potential long-term [3] disability or death. Strokes can result in a wide range of impairments, including difficulties with speech, movement and cognition [4] depending on the area of the brain affected. Early recognition of stroke symptoms and prompt treatment are critical in minimizing brain damage and improving outcomes for stroke patients.

Brain strokes occur primarily due to two major mechanisms [5] ischemia and haemorrhage. Around 85% of those are ischemic strokes occurring when the blood supply to the brain region is blocked [6] often by a blood clot or plaques. This blockage in turn has the effect of ramming

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the oxygen supply and nutrients from the rest of the body to the brain cells [7] the result is dead cells. Hemorrhagic strokes are, however, as a result of a burst blood vessel which causes bleeding within or around the brain. Thus, hypertension aneurism and arteriovenous [8] malformation may cause hemorrhagic strokes. Both could be caused by life styles such as smoking, obesity and lack of exercise or they [9] could be linked to other diseases such as diabetes heart disease, or high cholesterol. It is necessary to know these risk factors for their lower prevention and subsequent early identification.

Existing machine learning and deep learning approaches for brain stroke detection have made significant strides in improving diagnostic accuracy and efficiency. Traditional machine learning models, such as Support Vector Machines (SVM), Random Forest (RF), and Logistic Regression (LR), are widely used for tasks like stroke lesion segmentation, outcome prediction, and classification. These models often require extensive feature engineering and large amounts of labeled data to perform effectively. On the other hand, deep learning models, particularly Convolutional Neural Networks (CNNs), have revolutionized stroke detection by automating the extraction of complex patterns from raw medical images. CNN-based architectures like VGG, ResNet, and U-Net are commonly applied to detect and segment stroke lesions with high accuracy, reducing the need for manual feature extraction. These advancements in machine learning and deep learning continue to push the boundaries of stroke detection, although challenges remain in terms of interpretability and data integration.

Some of the innovative approaches of our motivation [10] using machine learning, deep learning and transfer learning have offered a boost to the identification of brain strokes by providing higher accuracy and faster diagnosis. Another technique involves [11] where a large amount of medical data is processed and at the end they determine features that could signal the onset of a stroke. Consists of the use of deep learning, specifically with convolutional neural networks [12] for analyzing medical images for more precise evidence of a stroke manifesting in CT scans and MRIs. Transfer learning enhances [13] this process by enabling the use of models, which have been originally trained on datasets, to provide a better foundation for training stroke-specific data. These techniques are reported to offer methodology [14] for creating algorithmic models of stroke detection that can help clinicians make a timely diagnosis and improve the outcome for patients.

We deploy a transfer learning-based mechanism to detect brain strokes by leveraging advanced neural network architectures. Initially, spatial features are extracted using the VGG-16 model, a deep convolutional neural network known for its robust performance in image classification tasks. These extracted features capture critical details and patterns relevant to brain stroke detection. Subsequently, the new feature set is transferred and processed using Gaussian Naive Bayes (GNB) combined with non-negative matrix factorization. This approach allows for effective dimensionality reduction and enhanced classification accuracy, leading to a more efficient and accurate detection system for brain strokes. The combination of VGG-16's powerful feature extraction capabilities and GNB's probabilistic classification, along with non-negative matrix factorization, ensures that the model not only identifies strokes with high precision but also operates efficiently on large datasets. This integration of transfer learning techniques significantly improves the reliability and speed of brain stroke diagnosis, facilitating timely medical intervention and potentially saving lives.

Our main research contribution is as follows:

- An advance approach Novel Neuro-VGNB is proposed for transfer learning based mechanism on image data. The Neuro-VGNB first obtains the spatial Feature from the input visual modality. The features of the GNB classifier are combined with the help of non-negative matrix factorization in order to create a new feature set.
- For the evaluation, we have utilized CT scans dataset and also trained as well as tested deep learning model and four other modern machine learning models. To ensure that the above techniques is efficient, we used K-fold cross-validation. Moreover, we also analyzed the time complexity of all these approaches in order to analyze their efficacy.

II. LITERATURE ANALYSIS

The current review has aimed at trying to review and organize the findings in an effort to determine the existing gaps, trends as well as emerging themes that form the basis of the current study.Table 1 shows litreature studies.

The timely detection of a brain stroke [15] in MRI images can significantly improve patients' chance of surviving, meaning that this is an area that requires attention. Nevertheless, the automated detection is a potential issue because of shapes, sizes, and locations of the lesions in stroke. To respond to these issues, with regards to computer aided detection of ischemic stroke lesions, an optimized fuzzy level segmentation algorithm has been postulated to be used. It is also useful to divide the lesions properly in the correct manner in order to obtain multi textual features that constitute the final features. The weighted Gaussian Naïve Bayes classifier uses these features to distinguish between normal and pathological stroke lesion groups. According to experimental results, this technology outperforms current state-of-the-art procedures with a 98% efficacy rating. 32% accuracy, 96.87% sensitivity, and 98.82% F1 measure. This demonstrates the proposed classifier's applicability in terms of the rate of differentiation between the normal and abnormal classes.

Diagnosis of stroke using MRI [16] special under DWI sequences. Their approach also employed decision- making algorithm which include segmentation and classification components only. They classified strokes into three categories. There are three basic forms of stroke.Among the several kinds of stroke are the entire anterior circulation stroke, the lacunar syndrome, and the partial anterior circulation syndrome. In segmentation, expectation-maximization algorithm was used to segment this image as it yielded better segmentation of the areas of the stroke.Still to improve the detection accuracy they used the unique fractional-order Darwinian particle swarm optimisation method. In this sense, the features were categorised using the following schemes which have been extracted from different segmented areas: SVM RF classifiers in classification phase. To achieve this objective, this study was able to yield a relatively high level of accuracy of 93. 4% with RF classifier making their paper resourceful by describing how their method contributed towards improved stroke detection with image processing and machine learning techniques.

Introduced an emerging spiking neural network [17] reservoir to forecast cases and generate individual spectro-temporal profiles. It stems from the fact that they hold some properties of SNNs which can be harnessed to enhance the accuracy of the forecasting. The comparative analyses of the proposed method with other conventional machine learning method Multiple Linear Regression, MLP, and SVM are to be presented here. These experimental findings demonstrated that this new kind of dynamic spiking neural network reservoir system has outperformed this previous approach and other methods to deliver a remarkable accuracy of 94%. It also proves that there is still space to go for more elaborate neural network architectures as a way of improving the strength of the power of prediction across numerous data states.

Segmentation of the ischemic region in medical [18] images by using a deep fully convolutional network through a supervised means. In their study, they made use of the Leaky Rectified Linear Unit (Leaky ReLU) activation functions in the last two layers of the used network architecture as this will enable the construction of extra features that are not usually created in the U-net architecture. This brought in better capacity of the network in learning difficult patterns that are related to the ischemic areas. Therefore, the authors successfully précised the correlation between the algorithms using the Dice coefficient, equal to 0, in the best case. 70, proving how their proposed method helped in improving the level of segmentation needed for raising the level of accuracy in the diagnosis of strokes and the development of the right treatment strategies for patients.

Suggested a new method to extract out [19] features from proposals which led them to achieve radiological density of the brain and he suggested to name this new assessment as Analysis of Brain Tissue Density. Besides, they utilized it to extract the features of the brain CT image for various works: Further, for assessing their proposed method, they employed five machine learning algorithms: Now the following algorithms are described: MLP is an ANN used for binary and non-binary classification tasks, SVM was developed for classification, regression, and density estimation, kNN is also classification, and OPF is the selection of an optimum path in trees. This they were able to attain a perfection of a hundred percent accuracy of the data though there is always room for errors in typing.

The stroke-associated pneumonia data is obtained and [20] automatically labeled. The data set is split during pre-processing into a training and a validation or test data set. Using five ML techniques—logistic regression, random forest classifier, XGBoost and fully connected deep neural network (DNN)—they then categorised the data. Her. In the work of the writers, the experimental results revealed the best accuracy of 76%. Female participants' cross-validated AUC results through the proposed system with SD of 3% less than the use of DNN; conversely, the study revealed that proposed the system was able to attain maximum AUC of 0. 841 utilizing XGBoost.

Random collections of the CT images of the brain [21] from the patients were obtained.In the work, they proposed CNN architectures for the three classes and for the categorization of brain CT images. They also divided it into testing and training sets, used 10-fold cross-valuation, and generated two datasets: in dataset 1 the classes were dichotomized as hemorrhagic and ischemistically and in dataset 2 there were three classes including; hemorrhagic, ischemically and normal. Moreover, they obtained 98 % accuracy even using the tenfold cross-valuation for dataset 1. The accuracy was found to be 92 when the equivalent procedures were used on dataset 2.In this paper, the author used "Dataset 1 and Dataset 2" for the model evaluation. Two different datasets are used when the proposed model is applied in Dataset 1 the accuracy score is good but when applied to Dataset 2 the proposed model decreases the accuracy score.

There have been attempts towards [22] performing optimized artificial intelligence algorithms to support the identification of stroke. This paper also describe the new classification model of OzNet CNN that comes with the machine learning algorithm to classify the images of brain stroke's CT with binary classification. As stated, our analysis also revealed that OzNet was effective in its function particularly when complemented with the application of using the minimum RM, R method and with such classifiers as DT, kNN, LDA, NB, and SVM. The fully connected layer of OzNet output 4096 important features which is reduced by using mRMR method up to 250 features. They were then classified or categorized utilizing the above-discussed machine learning algorithms. Of all, the integrated algorithm, OzNet-mRMR-NB was outstanding with accuracies of 98%. 42%andtheAUCof0. 99% demonstrated the effectiveness of the developed stroke detection model from the radiology images of the brain CT scans.

Proposed framework and the set [23] of base ideas are aimed to enable an efficient identification of the brain stroke by using deep CNN models such as VGG16, ResNet50, DenseNet121. Specifically, the most promising configurations of models belonging to the deep CNN class are tailored to address requirements set in the context of the brain stroke prediction challenge. All the employed deep learning models are further fine-tuned for achieving more superior results. We also propose Optimised Deep Learning for Brain Stroke Detection (ODL-BSD) method with which the models can be enhanced even further. To validate the proposed framework, the acquired MRI images are employed. Further, it was observed that all deep CNN models were improved significantly with the proposed methods. This may also change in the future based on the findings of the identified studies above. The fifth area refers to the techniques employed to enhance the capacity of Deep Learning models to predict influencing factors, and this should be the future trend for research. This can be done for instance by scaling the models. The score of the proposed model is 95 which is quite impressive at getting higher results.

Stroke is one of the most fatal [24] conditions existing, the consequence of the disruption of blood delivery to the brain due to a blocked vessel or bleeding. Due to the possible unfavourable outcomes in the patient's condition, time plays a critical role in stroke, including the need for early diagnosis and treatment. Stroke Classification using the Deep Learning Focus of this chapter is architectures on the Brain Stroke CT Dataset. 2501 brain stroke computed tomography (CT) pictures in all were used in test and training stages of the study. To differentiate between normal and stroke related CT images, its proposed to use several high-performance Deep Learning CNNs which were pretrained and includes GoogleNet, AlexNet, VGG 16, VGG 19 and Residual CNN.The use of VGG-19 yielded the highest classification accuracy and provided an ACC of 97. 06%, SEN of 97. 41%, SPE of 96. Precisely, the average of the recall metric, known as the R-score, is 49% and the F-score is 96. 95% which proves that it is effective in detecting the stroke in the brain CT images.

Machine learning techniques have become prominent [25] in the current world for the use in the detection of stroke. It can be noted that the primary focus of modern research is to search for the best algorithms, methods, and features that can help clinicians make correct decisions in the sphere of stroke prevention and treatment. Toward this end, an improved early stroke detection method based on brain CT images, genetic algorithm, and BiLSTM model have been proposed. This system integrates a genetic method grounded on neural networks to consider the most suitable features seen by image classification and by means of those features, there is the formation of the BiLSTM model., The effectiveness of the system was analyzed by cross-validation and the parameters measured mainly included accuracy, precision, recall, F1 score, ROC AUC and the model obtained a final accuracy of 96. 5% accuracy rate. Further, the performance of the proposed model was benchmarked with traditional models the potential of this model was assessed as a diagnostic tool to assist physicians in stroke detection was confirmed.

This work investigates the use of CNN for the [26] classification of brain stroke using CT images. Since the research uses a various dataset, the results determine whether the developed CNN model distinguishes between 'Normal' and 'Stroke' image categories. For assessment, the accuracy rate, precision, recall, and the F-value are employed to assess the model's diagnostic efficiency, which gives an all-rounded view of the performance of the Deep learning model. The study ensures that the training process is done comprehensively by paying attention to the learning rates and the model's stability, which is so important to help in reliable results. The obtained outcomes reflect a high degree of accuracy, and definite prejudice in terms of the high precision, recall factor, and F-score, all of which underline the possibility of increasing the effectiveness of stroke diagnostics based on deep learning. To this end, the research also responds to the difficulty of data availability by replacing lost data by similar data as practised and vital in improving model training. However, the researchers acknowledge the need for additional work with more samples and a sample variety and identify potential areas where model performance may be enhanced.

A. RESEARCH GAPS AND LIMITATIONS

After reviewing previous research, we discovered some gaps.

- Previous researchers used conventional research methods to Brain Stroke Disease Detection. Classical approaches of Deep Learning and Machine Learning is used without advancements.
- Employed DL models have higher computational complexity.
- It is important to recall new improved transfer learning methods and decrease the costs of computing. Also, the efficiency is low.

III. PROPOSED METHODOLOGY

The research methodology emphasizes the potential for identifying brain stroke using CT scan images, as illustrated in the figure 1. Initially, we gathered a dataset comprising normal and stroke images. Basic preprocessing is applied to this dataset. Following the preprocessing phase, new features were extracted from the images using transfer learning. These newly derived features were then categorized and split into 80% for training and 20% for testing machine learning and deep learning models.The model that exhibited the best performance is chosen for the effective identification of brain stroke disease.

A. BRAIN STROKE IMAGE DATASET

For our study, we leveraged a publicly [27] accessible dataset of CT scan images available online. Figure 2 shows target labels. This dataset includes a total of 2,501 images divided into two categories. 1,551 images depict normal brain scans while 950 images represent brain scans with stroke conditions. This dataset provided a robust foundation for training and evaluating our machine learning and deep learning models. By utilizing such a well-rounded dataset, we aimed to enhance the accuracy and reliability of our brain stroke detection model.

TABLE 1. The literature analysis based on state-of-the-art approaches performance.

Ref	Year	Proposed Technique	Dataset	Accuracy Score	Research Gap
[15]	2021	GNB	MRI images datset	98%	Classical approach is used.
[16]	2020	RF	MRI image dataset	93.4%	Classical approach is used.
[25]	2024	Bilstm	Brain CT scans dataset	94.0%	Computational cost is high.
[26]	2024	CNN	CT images dataset	98%	Classical neural network is used.
[20]	2020	DNN	MRI scans	76.0%	Accuracy score is poor.
[21]	2021	CNN	CT scans dataset 1 and dataset 2	92.0%	Poor performance when applied in dataset 2.
[22]	2022	Oznet	CT scans dataset	93.0%	Accuracy score is low.
[23]	2024	VGG16	CT scans Dataset	95.0%	Computational cost is high.
[24]	2023	Alexnet	CT scans Dataset	97.0%	Traditional method is used to address this problem.

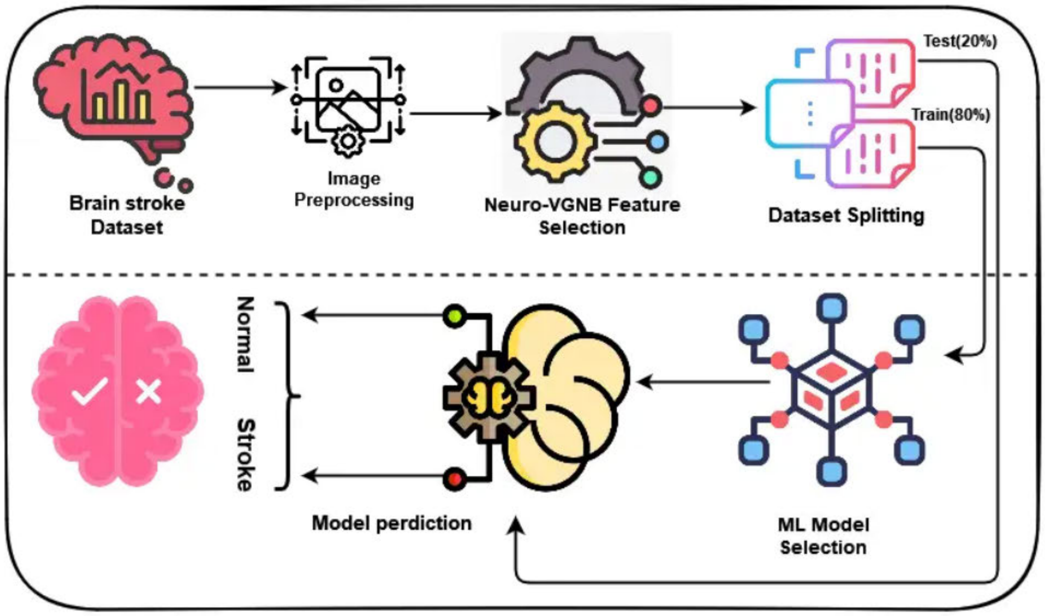


FIGURE 1. Our innovative approach methodology for the brain stroke detection.

B. IMAGES PROCESSING

Figure 3 shows image analysis after preprocess.We conducted simple image preprocessing to enhance the analysis [28] of multimodal data. We imported brain stroke image data and identified the total number of files in each labeled directory. During this process, we proportionally rescaled all imported images. For resizing, the pixel information of the images was converted to NumPy arrays and then to tensors. We assigned numerical labels to the images, designating ''Normal'' as 0 and ''Stroke'' as 1. Following this, we split the data into training and test sets, maintaining an 80/20 split.

C. PROPOSED TRANSFER APPROACH

The workflow of the proposed transfer learning-based architecture, Neuro-VGNB, is detailed step-by-step in Figure 4. Initially, image data from Brain stroke is processed using VGG16 to extract spatial features. This transforms the input image set into a thousand new spatial features. Next, Non-Negative Matrix Factorization (NMF) decomposes the feature space into two non-negative matrices, selecting features with large variance values. These spatial features are then input into the Gaussian Naive Bayes (GNB) classifier, where transfer features are developed. Consequently, features from both NMF and the Gaussian Naive Bayes (GNB) classifier are used together to develop the overall machine learning techniques. According to our findings, the proposed transfer learning methodologies improve accuracy in diagnosing brain strokes.

In our approach, NMF is first applied as a feature extraction method to reduce the dimensionality of the input data while preserving the essential patterns. This step is crucial for handling high-dimensional datasets, as it transforms the original features into a lower-dimensional representation that is more manageable and interpretable. Once the features are extracted using NMF, these transformed features are then fed into a Gaussian Naive Bayes (GNB) classifier.The GNB model is chosen for its efficiency and robustness in handling

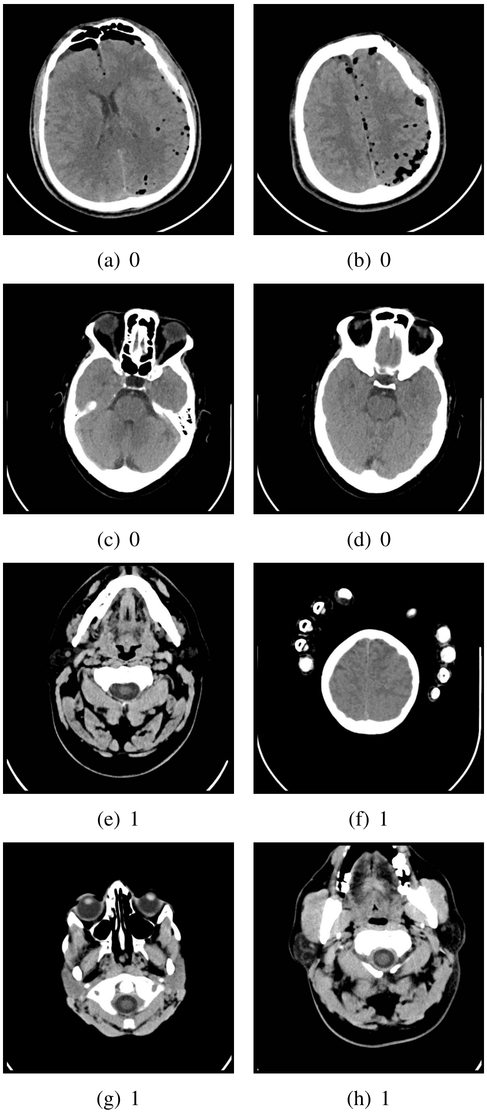


FIGURE 2. Sample images from the dataset (0) indicate normal and (1) indicate stroke.

probabilistic feature sets, which align well with the output of NMF. By applying GNB, we leverage its ability to model the likelihood of the data belonging to different classes based on the Gaussian distribution of the features. This combination of NMF and GNB allows for an effective and computationally efficient classification process, where NMF enhances feature interpretability and GNB ensures reliable classification based on the probabilistic distribution of the reduced feature set.

D. APPLIED LEARNING APPROACHES

Artificial Intelligence (AI) techniques for brain stroke detection leverage advanced algorithms to analyze images with high accuracy. These methods use machine learning models like VGG-16 to extract intricate details from brain stroke images. By independently learning and recognizing subtle patterns in brain stroke characteristics, AI significantly boosts the precision and effectiveness of stroke detection.

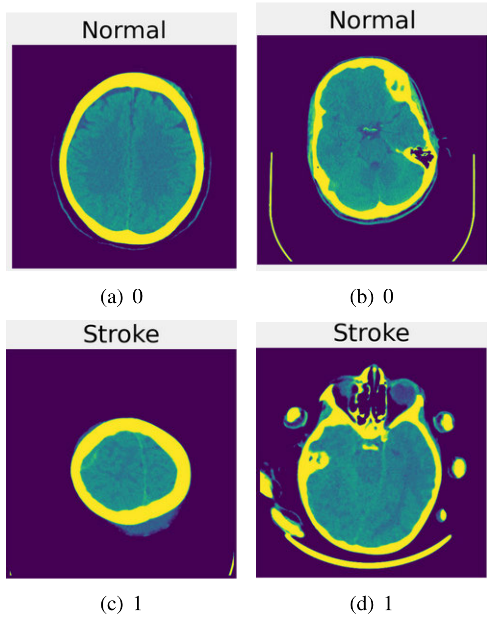


FIGURE 3. Sample images after image preprocessing (0) indicate normal and (1) indicate stroke.

E. LOGISTIC REGRESSION

A Logistic Regression (LR) model can effectively be used [29] for the detection of brain stroke by classifying images as either normal or indicative of a stroke. This model operates by analyzing the input features extracted from brain imaging data and assigning a probability to each class. The LR model uses a sigmoid function to map the input features to a probability value between 0 and 1, representing the likelihood of the image showing a stroke. The model is trained on labeled data, adjusting its parameters to minimize the error in its predictions. By learning the relationship between the input features and the target labels, the LR model can accurately classify new, unseen images as either normal or stroke. The logistic regression model can be mathematically expressed as:

$$P(y = 1 \mid X) = \frac{1}{1 + e^{-(w_0 + w_1 x_1 + w_2 x_2 + \cdots + w_n x_n)}} \tag{1}$$

where $P(y = 1 \mid X)$ is the probability of the image being classified as a stroke, w_0 is the intercept, $w_1, w_2, \ldots, w_n$ are the weights, and $x_1, x_2, \ldots, x_n$ are the input features.

F. GAUSSIAN NAIVE BAYES

A Gaussian Naive Bayes (GNB) model is an effective [30] method for detecting brain strokes by classifying images as either normal or indicative of a stroke. This model operates under the assumption that the features follow a Gaussian (normal) distribution. By analyzing the pixel intensity values of brain images, the GNB model calculates the probability of each feature belonging to a particular class (normal or stroke). The model then combines these probabilities to make a final classification decision. Training the GNB model involves estimating the mean and variance of the features for each

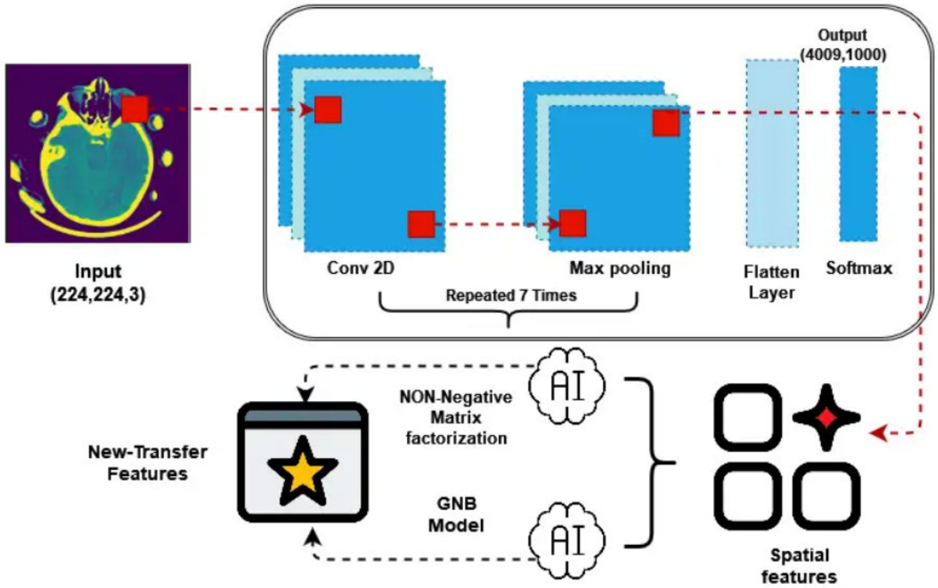


FIGURE 4. **Our proposed architectural analysis of the workflow for our innovative feature engineering process for the brain stroke detection.**

class, allowing the model to predict the likelihood of new, unseen images being classified as normal or stroke. For the Gaussian distribution, $P(x_i \mid y)$ is given by:

$$P(x_i \mid y) = \frac{1}{\sqrt{2\pi\sigma_y^2}} \exp\left(-\frac{(x_i - \mu_y)^2}{2\sigma_y^2}\right) \tag{2}$$

where $P(y \mid x_1, x_2, \ldots, x_n)$ is the posterior probability of class y given the features $x_1, x_2, \ldots, x_n$, $P(y)$ is the prior probability of class y, $P(x_i \mid y)$ is the likelihood of feature x_i given class y, and μ_y and σ_y^2 are the mean and variance of the features for class y, respectively.

G. RANDOM FOREST

A Random Forest (RF) model is highly effective for [31] detecting brain strokes by classifying images as either normal or indicative of a stroke. This model utilizes an ensemble of decision trees, each trained on different subsets of the data and features, to make predictions. By aggregating the outputs of multiple trees, the RF model improves accuracy and reduces the risk of overfitting. It analyzes various features from brain imaging data to determine the likelihood of a stroke. During the training phase, the RF model learns the relationships between the features and the target labels, enabling it to make accurate classifications on new, unseen images.

The Random Forest model can be mathematically expressed as:

$$\hat{f}(x) = \frac{1}{T}\sum_{t=1}^{T} f_t(x) \tag{3}$$

where $\hat{f}(x)$ is the aggregated prediction of the ensemble, T is the total number of decision trees in the forest, and $f_t(x)$ is the prediction from the t-th decision tree for input x.

H. GRADIENT BOOSTING CLASSIFIER

A Gradient Boosting Classifier is a powerful technique [32] for detecting brain strokes by classifying images as either normal or indicative of a stroke. This model builds an ensemble of decision trees sequentially, where each tree attempts to correct the errors made by the previous ones. By focusing on the residuals or errors from prior models, Gradient Boosting gradually improves the accuracy of the predictions. It efficiently handles complex patterns in brain imaging data, making it well-suited for stroke detection. During training, the model learns the relationships between features and target labels, allowing it to make precise classification images. The Gradient Boosting model can be mathematically expressed as:

$$F_m(x) = F_{m-1}(x) + \nu \sum_{j=1}^{J} \gamma_{jm} I(x \in R_{jm}) \tag{4}$$

where $F_m(x)$ is the updated model after the m-th iteration, $F_{m-1}(x)$ is the model from the previous iteration, ν is the learning rate, γ_{jm} is the weight applied to the j-th region R_{jm} of the m-th tree, and $I(x \in R_{jm})$ is an indicator function that equals 1 if x belongs to region R_{jm}, and 0 otherwise.

I. VISUAL GEOMETRY GROUP-16

The VGG16 model is a convolutional neural network [33] architecture that is highly effective for image classification tasks, including the detection of brain strokes. This model

TABLE 2. Hyperparameters used in different techniques.

Technique	Hyperparameter
GBC	`loss='log-loss', max_depth=3, learning_rate=0.3, criterion='friedman'`
LR	`copy_X=True, fit_intercept=True, positive=False, normalize=False`
RF	`max_depth=300, n_estimators=100, criterion='gini', num_leaves=31, learning_rate=0.1`
GNB	`var_smoothing=1e-9`
$VGG-16$	`input_shape=(224,224,3), hidden_layer_sizes=(100), activation='ReLU', optimizer='Adam', alpha=0.0001, learning_rate='constant'`

consists of 16 layers, including multiple convolutional layers, pooling layers, and fully connected layers. By leveraging its deep architecture, VGG16 is capable of extracting intricate features from brain imaging data, which are essential for differentiating between normal and stroke-affected images. The model is pre-trained on a large dataset, allowing it to learn rich feature representations that can be fine-tuned for specific tasks like stroke detection. During the training phase, VGG16 learns to optimize its weights through backpropagation, enhancing its accuracy in identifying strokes.

$$y = \text{softmax}\left(W_n \cdot \text{ReLU}\left(W_{n-1} \cdot \ldots + b_{n-1}\right) + b_n\right) \quad (5)$$

In this equation, y is the final output representing the probabilities for each class. The variables $W_1, W_2, \ldots, W_n$ are the weights of each layer, while $b_1, b_2, \ldots, b_n$ are the corresponding biases. The activation function ReLU is applied at each layer, and the final output is processed through a softmax function to yield the class probabilities.

J. HYPERPARAMETER TUNNING

The machine learning algorithms employed in this study [34] involve selecting the most suitable hyperparameters. We optimized each approach's parameters using k-fold cross-validation, along with regular backups and advanced testing and training methodologies. Our research findings suggest that fine-tuning these hyperparameters leads to improved performance scores for detecting brain stroke images.Table 2 summarizes the hyperparameters used for various machine learning and deep learning techniques. For Gradient Boosting Classifier (GBC), loss='log-loss' specifies the loss function, maxdepth='3' limits the depth of trees, learning-rate='0.3' controls the step size, and criterion='friedman' is the function to measure the quality of splits. In Logistic Regression (LR), copy-x='True' ensures that the input features are copied, intercept='True' includes an intercept term, Positive='False' specifies no constraints on positivity, and Normalize='False' indicates that feature normalization is not applied. The Random Forest (RF) model uses max-depth=300 to set the maximum depth of trees, n-estimators=100 to determine the number of trees, criterion='gini' for the split quality measure, num-leaves=31 to limit the number of leaf nodes, and learning-rate=0.1 for the learning step size. Gaussian Naive Bayes (GNB) uses var-smoothing=1e-9 to avoid division by zero by smoothing the variance. For VGG-16, input-shape="224,224,3" specifies the dimensions of the input images, hidden-layer-sizes=(100) indicates the number of units in hidden layers, activation='ReLU' is the activation function, Optimizer='Adam' is the optimization algorithm, alpha=0.0001 is the regularization parameter, and learning-rate='constant' maintains a constant learning rate.

IV. RESULTS AND DISCUSSIONS

In this section we briefly discuss the result of our innovative approach.

A. EXPERIMENTAL SETUP

In our experiment the Google Colab is utilized as a cloud-based platform that implements Jupyter Notebook. Table 3 shows the specification. The performance of the machine learning approach is measured using several measures among them being accuracy, F1, precision and recall.

TABLE 3. The experimental setup information.

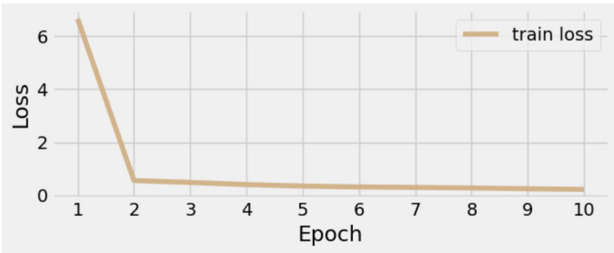
Specification	Value
Model	Dell Intel(R) CPU 3.20Ghz
ProgrammingLanguage	Python 3.0
CPUMHZ	3000
Cachevolume	5632KB
RAM	16 GB
CPUcore	2
AddressVolume	36bits Virtual , 64 bits Physical

B. VGG-16 MODEL PERFORMANCE

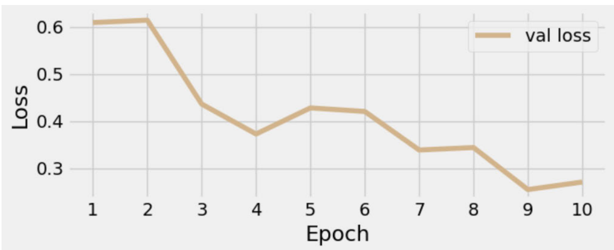
Figure 5 and Table 4 indicate the peformance analysis.The VGG16 model exhibits remarkable performance in brain stroke detection, achieving an accuracy of 89% on the original image dataset, with a log loss of 0.2219. This level of accuracy reflects the model's robustness in differentiating between normal and stroke-affected images, highlighting its effectiveness in medical imaging applications. The Figure 6 shows confussion matrix heatmap graph for perdiction analysis.To further enhance the model's precision, we extract features from the VGG16 architecture, which allows us to focus on the most informative aspects of the data. This feature extraction process captures intricate patterns and relationships within the images that may be indicative of a stroke. By utilizing these extracted features, we can fine-tune the model for specific classification tasks, improving its ability to detect subtle variations that could be crucial for accurate diagnosis.

TABLE 4. Performance analysis using VGG-16 on original data.

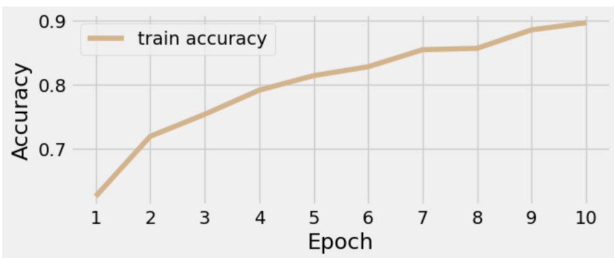
Models	Accuracy	Target Class	Precision	Recall	F1Score
VGG-16	0.89	Normal	0.88	0.86	0.92
		Stroke	0.93	0.80	0.86
		Average	0.89	0.88	0.89



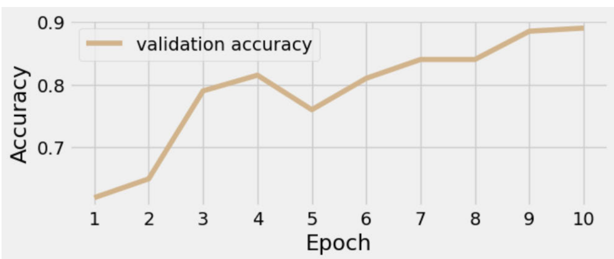
(a) Training loss



(b) Validation loss



(c) Train accuracy



(d) Validation accuracy

FIGURE 5. VGG-16 model performance analysis.

C. PERFORMANCE ANALYSIS USING SPATIAL FEATURE

Based on the analysis of the VGG16 results, we concluded that it can significantly enhance the overall accuracy.Table 5 shows performance results. These spatial features is subjected to various advanced machine-learning analyses, and the results are discussed in this paper. The findings indicate that the GNB method achieved a relatively high accuracy score, while the GBC method produced lower accuracy. Although this analysis demonstrates a noticeable improvement, it falls short of the expectations for deep fake image detection. Nevertheless, there remains considerable work to be done regarding more sophisticated transfer learning techniques that could further enhance these performance metrics.

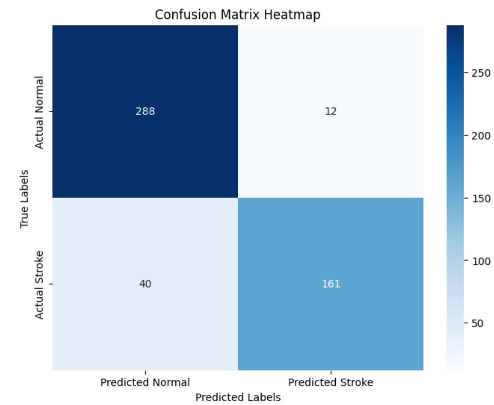


FIGURE 6. Confussion matrix heatmap graph analysis with original image data.

TABLE 5. Performance analysis with spatial feature.

Models	Accuracy	Target Class	Precision	Recall	F1Score
GBC	0.81	Normal	0.89	0.92	0.85
		Stroke	0.82	0.59	0.69
		Average	0.81	0.76	0.77
LR	0.66	Normal	0.70	0.75	0.75
		Stroke	0.60	0.60	0.60
		Average	0.66	0.66	0.66
GNB	0.73	Normal	0.79	0.78	0.78
		Stroke	0.64	0.65	0.65
		Average	0.73	0.73	0.73
RF	0.86	Normal	0.76	0.96	0.88
		Stroke	0.95	0.49	0.65
		Average	0.86	0.74	0.75

D. PERFORMNACE ANALYSIS WITH PROPOSED TRANSFER APPROACH

The comparisons conducted in the machine learning applications are detailed in the table 6 below, which outlines the models using the proposed Neuro-VGNB features. Notably, the results of the applied methods improved due to the innovative strategy introduced in this research. All methods mentioned achieved accuracy scores exceeding 0.99%. Specifically, the logistic regression (LR) technique used in this study outperformed others, achieving an impressive accuracy of 0.9996%. This indicates that the proposed approach leads to high-performance scores for detecting brain strokes from images.

Figure 7 displays a spider chart comparing classical spatial features with the newly proposed features based on T-test values. The result of this analysis demonstrate that the proposed method achieves high performance across all applications. The graph indicates that the suggested approach provides a significant improvement in performance accuracy.

TABLE 6. Performance analysis using our proposed new transfer features.

Models	Accuracy	Target Class	Precision	Recall	F1Score
GBC	0.99	Normal	0.99	0.99	0.99
		Stroke	0.99	0.99	0.99
		Average	0.99	0.99	0.99
LR	0.9996	Normal	0.99	1.0	1.0
		Stroke	1.0	1.0	1.0
		Average	0.9996	0.9996	0.9996
GNB	0.9952	Normal	1.0	0.99	0.99
		Stroke	0.99	1.0	1.0
		Average	0.9952	0.9952	0.9952
RF	0.99	Normal	0.99	0.99	0.99
		Stroke	0.99	0.99	0.99
		Average	0.99	0.99	0.99

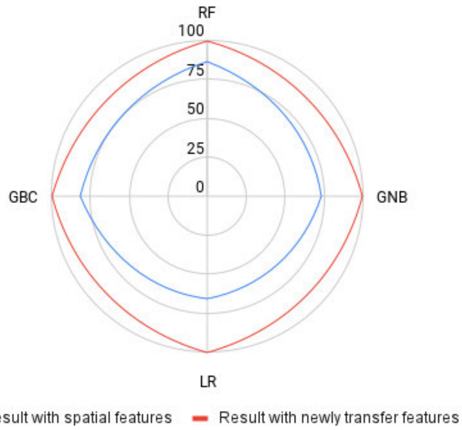


FIGURE 7. Shows spider chart analysis with spatial features and our proposed newly transferred features.

As illustrated in this research, we have achieved superior accuracy scores in all implemented procedures.

The performance evaluation is illustrated in Figure X, which presents the confusion matrix analysis of the methods applied using the newly introduced features. All techniques demonstrated effectiveness in reducing the error rate, thereby minimizing misclassification during the unseen test phase. This confirms the efficacy of the proposed logistic regression approach, which achieved a high correct classification rate and a low error rate compared to other available methods.

E. KFOLD VALIDATIONS ANALYSIS

We ultimately verified the performance scores of the applied machine learning methods using K-fold cross-validation, and the results are summarized in the table 7 below. We utilized 10 folds for validation. The analysis indicates that all applied methods achieved a K-fold accuracy exceeding 99.92%, with a standard deviation of 0.0000. This analysis supports the widespread application of the proposed Logistic Regression (LR) model for identifying brain stroke.

F. COMPUTATIONAL COMPLEXITY ANALYSIS

The time complexity of all applied methods is summarized in Table 8. The analysis revealed that the employed machine learning techniques exhibited lower performance in terms of time complexity. The GNB approach recorded a significantly high time complexity value of 2.25553. In contrast, the proposed Logistic Regression (LR) method developed in this paper successfully distinguishes between Normal and stroke images in a less duration, with a time complexity of 0.010015487.

TABLE 7. Our novel proposed shows state of the art k-fold validation analysis.

Technique	Kfold	K-Fod Accuracy (%)	Standard Deviation (%)
GBC	10	0.99	+/-0.0100
LR	10	1.0	+/-0.0000
Rf	10	0.99	+/-0.0100
GNB	10	0.99	+/-0.0100

TABLE 8. Our novel proposed shows computational complexity analysis.

Technique	Computation Time
GBC	0.24565386
LR	0.0100154876
Rf	0.648083448
GNB	2.255539

G. STATE OF THE ART STUDIES COMPARISONS

We evaluated the performance of our proposed solution in comparison to existing approaches found in the literature. Table 9 presents these comparisons with previous methods. The analysis indicates that while classical machine learning and deep learning techniques were frequently used in earlier research, this study employs advanced transfer learning mechanisms that utilize innovative strategies. The highest accuracy achieved previously was 98%. This analysis concludes that the approach presented in this paper significantly outperforms prior performance scores, as our proposed innovative technique achieved a performance score of 99.96

TABLE 9. Our proposed approach shows comparison with the state of the art past applied approaches.

Ref	Purposed Technique	Dataset	Accuracy Percentage
[15]	GNB	MRI image sdataset dataset	98.0
[16]	RF	MRI Image dataset	93.00
[24]	Alexnet	CT scans image dataset	97.0
[21]	CNN	CT images datasets	92.0
[23]	Vgg-16	CT scans dataset	95.0
[Our]	**Neuro-VGNB+LR**	**Brain Stroke Image dataset**	**99.96**

V. FEATURE SPACE ANALYSIS

In our analysis of the 3D feature space for brain stroke detection, we explore the multidimensional representation of

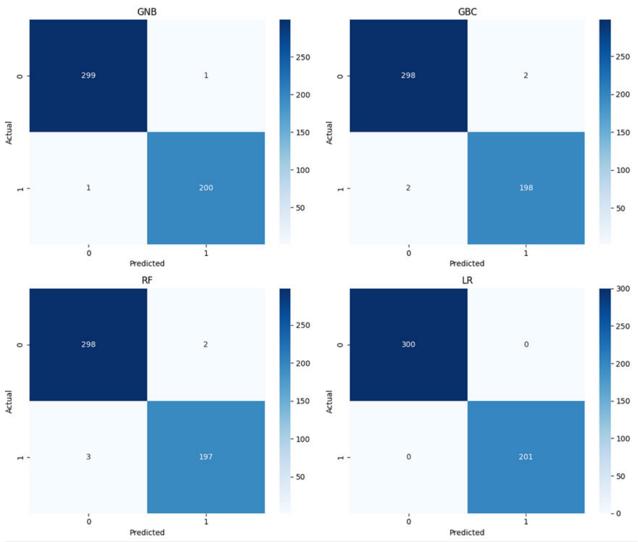


FIGURE 8. **Our Novel proposed shows a confusion matrix heatmap graph for the detection of brain stroke images.**

extracted features to enhance stroke classification accuracy. By projecting the high-dimensional feature vectors into a three-dimensional space, we visualize the distribution and separation of different classes, including stroke and normal cases. This 3D visualization facilitates a clearer understanding of the feature patterns and relationships between them. It allows us to identify clusters and overlaps among the classes, which is crucial for evaluating the effectiveness of our feature extraction methods and classification algorithms. The analysis reveals distinct separations between stroke and non-stroke features, indicating that our feature set captures significant information relevant to stroke detection. This spatial representation not only aids in validating the discriminative power of the features but also provides insights into potential areas for further refinement and optimization in our machine-learning model.

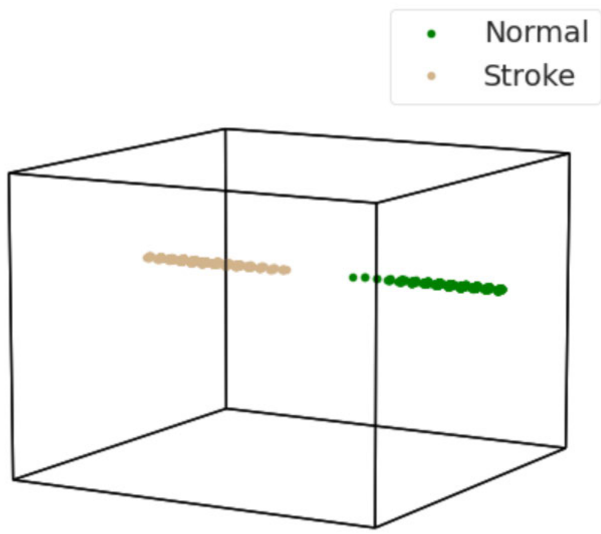


FIGURE 9. **The feature space analysis extracted new features from brain stroke images.**

Figure 9 displays the distribution of the corresponding feature vectors generated from the transfer feature set. These tests demonstrate that the features produced by the Neuro-VGNB method are linearly separable with a high degree of accuracy. It is noteworthy that there is a clear distinction in the separation of these features, contributing significantly to improved performance in detecting brain stroke images.

VI. CONCLUSION

This study successfully demonstrates the effectiveness of the Neuro-VGNB approach for brain stroke detection by integrating advanced deep learning and machine learning techniques. By utilizing the VGG16 model for feature extraction and enhancing these features through non-negative matrix factorization within the GNB framework, we achieved significant improvements in classification accuracy. The Logistic Regression model's outstanding accuracy score of 99.96% highlights the potential of our method in clinical applications. Furthermore, the application of k-fold cross-validation reinforces the reliability of our findings and positions our approach as a valuable tool for improving the early detection of brain strokes.

A. FUTURE WORK

Future work will focus on refining this model and exploring its applicability in real-world clinical settings to further enhance patient outcomes.

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REFERENCES

[1] K. P. Doyle, R. P. Simon, and M. P. Stenzel-Poore, "Mechanisms of ischemic brain damage," *Neuropharmacology*, vol. 55, no. 3, pp. 310–318, 2008.

[2] D. Radak, N. Katsiki, I. Resanovic, A. Jovanovic, E. Sudar-Milovanovic, S. Zafirovic, S. A. Mousad, and E. R. Isenovic, "Apoptosis and acute brain ischemia in ischemic stroke," *Current Vascular Pharmacol.*, vol. 15, no. 2, pp. 115–122, Jan. 2017.

[3] P. Vilela and H. A. Rowley, "Brain ischemia: CT and MRI techniques in acute ischemic stroke," *Eur. J. Radiol.*, vol. 96, pp. 162–172, Nov. 2017.

[4] P. J. Hand, J. Kwan, R. I. Lindley, M. S. Dennis, and J. M. Wardlaw, "Distinguishing between stroke and mimic at the bedside: The brain attack study," *Stroke*, vol. 37, no. 3, pp. 769–775, Mar. 2006.

[5] K. S. Wong, L. R. Caplan, and J. S. Kim, "Stroke mechanisms," in *Intracranial Atherosclerosis: Pathophysiology, Diagnosis Treatment*, vol. 40, 2016, pp. 58–71.

[6] P. Cui, L. D. McCullough, and J. Hao, "Brain to periphery in acute ischemic stroke: Mechanisms and clinical significance," *Frontiers Neuroendocrinol.*, vol. 63, Oct. 2021, Art. no. 100932.

[7] R. Jin, G. Yang, and G. Li, "Molecular insights and therapeutic targets for blood–brain barrier disruption in ischemic stroke: Critical role of matrix metalloproteinases and tissue-type plasminogen activator," *Neurobiol. Disease*, vol. 38, no. 3, pp. 376–385, Jun. 2010.

[8] Y. Li, W. Zhong, Z. Jiang, and X. Tang, "New progress in the approaches for blood–brain barrier protection in acute ischemic stroke," *Brain Res. Bull.*, vol. 144, pp. 46–57, Jan. 2019.

[9] R. Fujimoto, E. Suzuki, S. Kashima, N. Kazufumi, T. Oka, H. Ito, and T. Yorifuji, ''Ambient heat exposure after the rainy season is associated with an increased risk of stroke,'' *Eur. Heart J.*, vol. 44, no. 1, Jan. 2023, Art. no. ehac779087.

[10] A. Raza, K. Munir, M. S. Almutairi, and R. Sehar, ''Novel transfer learning based deep features for diagnosis of down syndrome in children using facial images,'' *IEEE Access*, vol. 12, pp. 16386–16396, 2024.

[11] I. Sánchez Fernández and J. M. Peters, ''Machine learning and deep learning in medicine and neuroimaging,'' *Ann. Child Neurol. Soc.*, vol. 1, no. 2, pp. 102–122, Jun. 2023.

[12] R. Maskeliunas, R. Damasevicius, A. Paulauskas, M. G. Ceravolo, M. Charalambous, M. Kambanaros, E. Pampoulou, F. Barbabella, A. Poli, and C. V. Carvalho, ''Deep reinforcement learning-based iTrain serious game for caregivers dealing with post-stroke patients,'' *Information*, vol. 13, no. 12, p. 564, Nov. 2022.

[13] M. M. Afsar, S. Saqib, Y. Y. Ghadi, S. A. Alsuhibany, A. Jalal, and J. Park, ''Body worn sensors for health gaming and e-learning in virtual reality,'' in *Proc. CMC*, 2022.

[14] S. M. Aslam, A. K. Jilani, J. Sultana, and L. Almutairi, ''Feature evaluation of emerging E-learning systems using machine learning: An extensive survey,'' *IEEE Access*, vol. 9, pp. 69573–69587, 2021.

[15] S. Jayachitra and A. Prasanth, ''Multi-feature analysis for automated brain stroke classification using weighted Gaussian Naïve Bayes classifier,'' *J. Circuits, Syst. Comput.*, vol. 30, no. 10, Aug. 2021, Art. no. 2150178.

[16] A. Subudhi, M. Dash, and S. Sabut, ''Automated segmentation and classification of brain stroke using expectation-maximization and random forest classifier,'' *Biocybernetics Biomed. Eng.*, vol. 40, no. 1, pp. 277–289, Jan. 2020.

[17] N. Kasabov, V. Feigin, Z.-G. Hou, Y. Chen, L. Liang, R. Krishnamurthi, M. Othman, and P. Parmar, ''Evolving spiking neural networks for personalised modelling, classification and prediction of spatio-temporal patterns with a case study on stroke,'' *Neurocomputing*, vol. 134, pp. 269–279, Jun. 2014.

[18] R. Karthik, U. Gupta, A. Jha, R. Rajalakshmi, and R. Menaka, ''A deep supervised approach for ischemic lesion segmentation from multimodal MRI using fully convolutional network,'' *Appl. Soft Comput.*, vol. 84, Nov. 2019, Art. no. 105685.

[19] P. P. R. Filho, R. M. Sarmento, G. B. Holanda, and D. de Alencar Lima, ''New approach to detect and classify stroke in skull CT images via analysis of brain tissue densities,'' *Comput. Methods Programs Biomed.*, vol. 148, pp. 27–43, Sep. 2017.

[20] X. Li, M. Wu, C. Sun, Z. Zhao, F. Wang, X. Zheng, W. Ge, J. Zhou, and J. Zou, ''Using machine learning to predict stroke-associated pneumonia in Chinese acute Ischaemic stroke patients,'' *Eur. J. Neurol.*, vol. 27, no. 8, pp. 1656–1663, 2020.

[21] A. Gautam and B. Raman, ''Towards effective classification of brain hemorrhagic and ischemic stroke using CNN,'' *Biomed. Signal Process. Control*, vol. 63, Jan. 2021, Art. no. 102178.

[22] O. Ozaltin, O. Coskun, O. Yeniay, and A. Subasi, ''A deep learning approach for detecting stroke from brain CT images using OzNet,'' *Bioengineering*, vol. 9, no. 12, p. 783, Dec. 2022.

[23] S. R. Polamuri, ''Stroke detection in the brain using MRI and deep learning models,'' *Multimedia Tools Appl.*, pp. 1–18, May 2024.

[24] A. Diker, A. Elen, and A. Subasi, ''Brain stroke detection from computed tomography images using deep learning algorithms,'' in *Applications of Artificial Intelligence in Medical Imaging*. Amsterdam, The Netherlands: Elsevier, 2023, pp. 207–222.

[25] M. A. Saleem, A. Javeed, W. Akarathanawat, A. Chutinet, N. C. Suwanwela, W. Asdornwised, S. Chaitusaney, S. Deelertpaiboon, W. Srisiri, W. Benjapolakul, and P. Kaewplung, ''Innovations in stroke identification: A machine learning-based diagnostic model using neuroimages,'' *IEEE Access*, vol. 12, pp. 35754–35764, 2024.

[26] A. Tursynova, A. Sakhipov, I. Omirzak, Z. Ikram, S. Smakova, and M. Kutubayeva, ''Classification of brain strokes in computed tomography images utilizing deep learning,'' in *Proc. IEEE 4th Int. Conf. Smart Inf. Syst. Technol. (SIST)*, May 2024, pp. 328–333.

[27] A. Rahman. *Brain Stroke CT Image Dataset*. [Online]. Available: https://www.kaggle.com/datasets/afridirahman/brain-stroke-ct-image-dataset

[28] M. J. McAuliffe, F. M. Lalonde, D. McGarry, W. Gandler, K. Csaky, and B. L. Trus, ''Medical image processing, analysis and visualization in clinical research,'' in *Proc. 14th IEEE Symp. Comput.-Based Med. Syst. (CBMS)*, Jun. 2001, pp. 381–386.

[29] A. B. Amjoud and M. Amrouch, ''Transfer learning for automatic image orientation detection using deep learning and logistic regression,'' *IEEE Access*, vol. 10, pp. 128543–128553, 2022.

[30] F.-Z. Nakach, H. Zerouaoui, and A. Idri, ''Binary classification of multi-magnification histopathological breast cancer images using late fusion and transfer learning,'' *Data Technol. Appl.*, vol. 57, no. 5, pp. 668–695, Nov. 2023.

[31] A. W. Salehi, S. Khan, G. Gupta, B. I. Alabduallah, A. Almjally, H. Alsolai, T. Siddiqui, and A. Mellit, ''A study of CNN and transfer learning in medical imaging: Advantages, challenges, future scope,'' *Sustainability*, vol. 15, no. 7, p. 5930, Mar. 2023.

[32] S. Basu, M. Gupta, P. Rana, P. Gupta, and C. Arora, ''Surpassing the human accuracy: Detecting gallbladder cancer from USG images with curriculum learning,'' in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2022, pp. 20854–20864.

[33] D. Albashish, R. Al-Sayyed, A. Abdullah, M. H. Ryalat, and N. A. Almansour, ''Deep CNN model based on VGG16 for breast cancer classification,'' in *Proc. Int. Conf. Inf. Technol. (ICIT)*, Jul. 2021, pp. 805–810.

[34] R. Hossain and D. Timmer, ''Machine learning model optimization with hyper parameter tuning approach,'' *Glob. J. Comput. Sci. Technol. D Neural Artif. Intell*, vol. 21, no. 2, p. 31, 2021.

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