International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 06 | June - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

A Survey on Deep Learning Techniques for the Stroke Prediction on Neuro Images

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ABSTRACT

Stroke is still one of the leading causes of death and chronic disability worldwide, and so immediate and proper diagnosis is a must to prevent delays in clinical management. Manual interpretation of imaging by conventional diagnostic methods is, by and large, time-consuming and susceptible to human bias. The medical imaging process has undergone a transformation in contemporary times due to the confluence of AI, ML, and DL approaches. Through computer-aided processing of CT and MRI scans, these have been shown to offer enormous potential to improve the detection, classification, and prediction of strokes.This survey paper provides a state-of-the-art overview of the AI-based models reported during the period from 2021 to 2024 in their methodologies, datasets, performance metrics, and clinical usability. By combining these contributions, the paper concludes that there are research gaps identified in current literature, including generalizability of models, a lack of standard datasets, and explainability requirements in clinical applications. This study aims to provide a foundation for further research into creating clinically integrated, interpretable, and reliable AI systems for stroke detection.

Index Terms- Stroke Detection, Deep Learning, Machine Learning, Neuroimaging, CT Scans, MRI, Artificial Intelligence, Medical Diagnosis, Hemorrhagic Stroke, Ischemic Stroke, Healthcare AI, Feature Extraction, Image Classification.

I.INTRODUCTION

Prompt and precise determination of stroke type and severity is crucial in guiding proper clinical interventions and reducing long-term neurological injury. Stroke, whether ischemic or hemorrhagic, requires immediate diagnosis to allow for life- saving therapies like thrombolysis or surgery. In the past, radiologists' manual interpretation of CT and MRI data has been a major factor in stroke diagnosis. While effective, this approach is unavoidably constrained by a series of limitations, including inter-observer variation, time to diagnosis, and dependence on specialist availability, particularly in low-resource settings. Medical image processing now offers tremendous new capabilities because to the growth of AI, especially ML and DL. These AI techniques offer a paradigm change from subjective, manual interpretation to scalable, automated, and objective diagnostic systems. In order to detect subtle and complicated aspects in neuroimages that could be challenging for the human eye to detect, DL models like CNNs, RNNs, and hybrid models are being used more and more.These models have demonstrated promising performance on stroke subtype identification, lesion localization, patient outcomes prediction, and even aiding treatment planning. Besides, AI algorithms may learn and refine their diagnosis from large extend of medical data in concurrent time, boosting the accuracy of diagnostics with time.Incorporation of such intelligent systems into clinical workflow has the prospect of reducing diagnosis time, increasing consistency, and enhancing overall health delivery.

Despite such advancements, there are still challenging barriers to deployment on a grand scale such as model interpretability, generalizability across diverse populations, and data privacy.on other imaging modalities such as MRI. Additionally, with the study, there is limited model explainability, which may discourage clinician adoption and trust.

II. EXISTING WORKS

1. Innovations in stroke identification: A machine learning-based diagnostic model using neuroimages.

This paper work introduces a new stroke diagnosis framework with the utilization of sophisticated machine learning models and neuroimaging data. The authors combine several pre-trained CNNs, such as AlexNet, VGG-19, InceptionV3, NASNetLarge, and ShuffleNet, to learn rich high-dimensional features of CT brain images. After selecting the most pertinent subset of these attributes using a Genetic Algorithm, a Bidirectional LSTM network is trained for classification. The model outperformed baseline classifiers such as Decision Trees, SVM, and Logistic Regression, achieving a very high classification rate of 96.5% on the test set.This hybrid approach has a number of benefits , first

,the deep CNNs used here guarantee capture of intricate spatial patterns within neuroimages efficiently. Second,the Genetic Algorithm significantly reduces feature dimensionality without losing informative attributes, thus enhancing computational efficiency and model performance. Third, BiLSTM's ability to capture temporal relationships enhances classification accuracy, particularly in stroke subtypes identification. These are advantages that make the system best suited for early diagnosis and decision-making in the clinical setting. Nevertheless, there are substantive limitations in the study.The data employed were a balanced but relatively small one, and this can preclude generalizability to large real-world populations.In addition, although the model works well on CT scans, it was never evaluated

Deep learning applied to intracranial hemorrhage detection.

This paper suggested a deep learning framework that enhanced accuracy and efficiency of intracranial hemorrhage (ICH) detection from CT imaging data. The authors suggested a CNN-based approach trained using annotated CT scans to automatically detect the presence or absence of hemorrhagic lesions. Image preprocessing, feature extraction by CNN layers, and diagnostic accuracy, sensitivity, and specificity-based performance evaluation were the methods adopted in their work. The model was effective, considering its potential application in high-pressure emergency clinical environments where diagnostic time is critical.May be the most significant benefit of this study is that it can save diagnostic time and eliminate human mistake, especially under high- pressure clinical settings. The model is also another tool for radiologists, which increases diagnostic confidence and accuracy more.Additionally, however, the paper also presents weaknesses, e.g., the relatively small training data set utilized, which can affect generalizability to diverse patient demographics. Additional authentication on bigger and spare disparate datasets is recommended, as the model's capacity to differentiate between multiple ICH subtypes was not fully validated. In spite of these constraints, the research presents a valuable contribution to AI-stroke diagnosis through evidence of the ability of deep learning models to identify life-threatening brain abnormalities.

2. Predicting brain stroke using IoT-enabled deep learning and machine learning: Advancing sustainable healthcare.

This paper introduce an IoT-based deep learning system for the prediction of stroke at an early stage based on magnetic resonance imaging (MRI) data. Conscious of the variability-sensitive and time-consuming nature of manual analysis of stroke, the researchers aim to develop an automated system that will enhance diagnostic efficiency and accuracy.The method followed is pre-processing of MRI scans and using DL architectures like DenseNet-121, ResNet-50, and VGG-16 to make stroke predictions.Out of the three, DenseNet-121 performed best with 96% accuracy, followed by ResNet-50 with 92%, and VGG-16 with 81%. The research also compares deep learning models with standard ML models such as SVM and Decision Trees, in which DL models exceed in terms of prediction skills.The incorporation of IoT allows real-time data input and analysis, hence the healthcare system becomes more responsive.However, the research provides some of the limitations including the need for more representative and broader datasets to increase model generalizability as well as more validation in diverse clinical settings. Some of the directions for future studies include dataset expansion and exploration of multimodal imaging techniques to increase the robustness and applicability of the prediction model.

3. Deep Learning-Enabled Brain Stroke Classification on Computed Tomography Images.

This paper presents a computer-aided diagnostic system based on CNNs for brain CT image classification into three categories: normal, ischemic stroke, and hemorrhagic stroke. Data augmentation methods like horizontal flip and real-time transformation through the Image Data Generator are utilized to augment the training set in the study.The model is prevented from overfitting using an early stopping approach. The CNN model provided

81% accuracy in the classification of brain strokes, testifying to the model's feasibility for use in clinical environments. To enable application in practice, the authors designed a web interface for a Python-based application in Streamlit and Ngrok to enable users to upload CT scans and obtain an immediate classification report. This alignment of deep learning with an ease-of-use interface speaks to the model's practicability for use in the real world. Yet, the work does recognize certain limitations, namely its dependence upon a fairly modest and possibly heterogenous dataset extracted from Kaggle, which is likely to impinge upon model generalizability. Moreover, although the model is promising for use in classification processes, its development must be further accomplished in terms of accuracy and testing the same across representative populations as well as across varying paradigms of imaging. Development of a more integrated system with detection, classification, and segmentation phases, using Internet of Things (IoT) devices and sophisticated models such as S-UNet for enhanced diagnostic outcome, is proposed in future work.

4. Sooty Tern Optimization Algorithm-Based Deep Learning Model for Diagnosing NSCLC Tumours.

This work introduces a new scheme of diagnosis of non-small cell lung cancer (NSCLC) by means of a hybrid deep model, which is tuned by Sooty Tern Optimization Algorithm (STOA). The proposed framework consists of several essential components: preliminary segmentation of lung nodules by Otsu method, feature extraction with improved Local Binary Pattern (LBP) algorithm, and classification by hybrid CNN and GRU network. The STOA significantly contributes to maximizing feature selection by imitating the attack and migratory behavior of sooty terns, thus increasing the diagnostic accuracy of the model. The latest SHOA-DNN model exhibits an excellent accuracy of 99.13%, surpassing the progressive benchmark models, according to consequence data based on the LIDC dataset. The combination of STOA makes the model more efficient through shorter training and inference times. Nonetheless, the research recognizes certain limitations, for example, validating across more diversified and larger data sets to generalize the findings. Further, the model's accuracy is high but has yet to be extensively tested in real clinical practice. Directions for future research involve investigating other optimization algorithms, like the Orca Predator Optimization Algorithm, to further enhance diagnostic performance.

5. Evaluation of techniques to improve a deep learning algorithm for the automatic detection of intracranial haemorrhage on CT head imaging.

This study designed and evaluated a DL model to improve the preprogrammed perception of ICH and their subtypes on NCCT head images. The authors applied a CNN based on the ResNeXt architecture, ImageNet pre- trained, using Python with the PyTorch library. To improve model performance, they employed a variety of strategies: windowing of images to simulate radiologist reading conditions, concatenation of slices to provide contextual cues from adjacent slices, and the addition of a RNN with BiLSTM layers to extract inter-slice relationships.The model was trained on the RSNA ICH Detection dataset of Kaggle and externally validated using the CQ500 dataset, which provides strong robustness to various imaging protocols and populations.

The combined CNN-RNN model, with both preprocessing methods, had a mean average precision (mAP) of 0.93 and an area under the receiver operating characteristic curve (AUC- ROC) of 0.966 for detecting any ICH. For certain subtypes such as intracerebral haemorrhage (ICH) and intraventricular haemorrhage (IVH), the model achieved AUC-ROCs of 0.983 and 0.991, respectively. In order to create saliency heatmaps and make the model easier to grasp by holding regions responsible for its predictions, the study also used gradient-weighted class activation mapping.calcifications or post- treatment alterations was not tested. The authors further stated that the prevalence of ICH in the datasets was higher than what is typically observed in a clinical setting, and this could impact the generalizability of the model's performance measures.

Despite these advancements, the study was not without certain limitations that were acknowledged. The datasets were showing class imbalances, particularly with fewer cases of extradural haemorrhage , which might affect the model's performance across these subtypes. The model's performance regarding the differentiation between haemorrhages and mimics like calcifications or post-treatment alterations was not checked. The authors further noted that the number of ICH in the datasets was greater than usual to be observed in clinics, and it has the potential to influence the generalizability of the model's performance metrics.Overall, this study demonstrates that some preprocessing steps and architectural design enhancements can significantly increase the performance of DL models to detect ICH on NCCT head scans. The interpretability of the model and high accuracy suggest that it could be valuable as a decision-making tool in clinical practice to enable the rapid and accurate diagnosis of intracranial haemorrhages.

6. A novel machine learning based feature extraction method for classifying intracranial hemorrhage computed tomography images. This paper suggest a novel method to improve the classification performance of ICH in CT images based on machine learning methods.The authors present a joint feature extraction approach that integrates transform-based and texture-based features to effectively extract the complicated patterns of ICH. Particularly, they use the Discrete Wavelet Transform , Discrete Cosine Transform, and Gray Level Co-occurrence Matrix to extract features and generate a detailed feature set capturing frequency and spatial domain information. The study uses the SMOTE, which generates synthetic samples to balance classes, to address class imbalance in the dataset.In addition, the Sequential Forward Feature Selection technique is used in order to determine the most important features, thus performing dimension reduction and increasing model performance.Machine learning classifiers based on ensemble methods, such as Random Forest, are used for classification. Among these, the Random Forest classifier is the best with an accuracy of 87.22% when a critical feature set of six features is applied.Although the method promises good results, the authors recognize some limitations. The research is mainly concerned with feature extraction and classification and does not explore segmentation of hemorrhage areas, which might further be used for increasing diagnostic accuracy. The model's validity in different datasets or authentic clinical settings must be established, and its accomplishment is also evaluated on a specific dataset.Future research may include combining segmentation methods and validating the model on varied datasets to check its stability and usability in a clinical setting.

7. Classification of intracranial hemorrhage CT images for stroke analysis with transformed and image-based GLCM features.

The paper introduces a hybrid feature extraction approach to enhance the classification accuracy of ICH in CT scans. The research combines transform-based features - namely DCT and DWT- with texture features obtained from the GLCM. The two are blended with the aim of obtaining both frequency and spatial domain information so that normal and hemorrhagic brain tissues can be differentiated.The authors used a dataset of 2,501 CT images, obtained from Kaggle, that included both hemorrhagic and normal cases. Preprocessing consisted of resizing the images and noise reduction using Gaussian filters. Feature extraction was performed by computing statistical features such as mean and standard deviation from the transformed images, and texture features from GLCM. These features were then combined to form hybrid feature vectors. For the purpose of classification, the ML algorithms such as Random Forest, Random Tree, and REPTree were utilized, with the experiments being performed using the WEKA tool. The Random Forest classifier had the highest accuracy with 87.89% when all the combined set of DWT and GLCM features were applied. This indicates that the hybrid approach is effective in extracting discriminant features that are useful for ICH detection.While, the study acknowledges some limitations. The small size of the dataset and possible scarcity of diversity will influence the generality of the model. Another limitation is the fact that this method is classifier-based only and does not cover segmentation methods with more precise localization of hemorrhage areas. Suggestions for future study directions include combination of segmentation and application of the model to diverse and larger data sets to raise its clinical impact.

8. An optimal deep learning framework for multi-type hemorrhagic lesions detection and quantification in head CT images for traumatic brain injury.

This paper offers an exhaustive deep learning- based solution to improving detection and quantification of different ICH subtypes in traumatic brain injury (TBI) patients.The pipeline proposed begins with the transformation of raw 3D DICOM CT data to NIfTI format for easier processing. A pre-trained multi-class semantic segmentation algorithm is then used to process each CT scan, producing accurate 3D masks that identify hemorrhagic areas. A feature refinement neural network next extracts the pertinent features from the input to classify ICH subtypes correctly as epidural (EDH), subdural (SDH), and intra parenchymal hemorrhages (IPH). Lastly, a quantitative measurement algorithm calculates important metrics like lesion volume and thickness, valuable in clinical decision-making. With an average accuracy of 96.21% across the three forms of hemorrhage, the system exhibited exceptional efficacy.Its ability to discriminate among various types of lesions is also a factor that helps in decreasing false-positive rates seen with earlier methods. In addition, computerized measurement of lesion parameters provides objective information available to guide emergency treatment options.Some limitations are, however, recognized. It has not yet been evaluated in broad clinical settings, and its effectiveness relies on the caliber and diversity of training data.Moreover, though the framework is useful for its quantitative estimates, it lacks clinical features like patient history and symptomatology, which would also make it more accurate in its diagnostic powers. Future studies involve combining multimodal data and large-scale clinical validations to further enhance the applicability of the framework to real-world settings.

9. Development of Machine Learning Models to Predict Probabilities and Types of Stroke at Prehospital Stage: The Japan Urgent Stroke Triage Score Using Machine Learning.

This article introduces an approach based on machine learning for improving prehospital stroke triage. The investigators performed a multicenter cohort study with eight model training centers. They employed logistic regression, random forests, and XGBoost algorithms for developing models for predicting four strokes: large vessel occlusion (LVO), ICH, subarachnoid hemorrhage, and cerebral infarction excluding LVO. The training cohort contained 3,178 patients and the test cohort contained 3,127 patients. With an area under the receiver operating characteristic curve value of 0.89 for both logistic regression and random forests, and 0.88 for XGBoost in the test cohort, the models demonstrated strong prediction performance, particularly in the case of LVO.These results surpassed those of previously published prediction models for LVO.Seven strengths of the interpretation encompass its enormous, heterogeneous sample and application of multiple machine learning algorithms, which promote the robustness and generalizability of the findings.There are also some limitations, such as needing further validation in different geographic and clinical settings to ensure more widespread applicability. Furthermore, although the models accurately predict stroke types, their integration into emergency medical services real-time workflows must be researched and developed further.Overall, the JUST-ML framework represents a significant advancement in prehospital stroke triage, offering an evidence-based tool to assist emergency medical personnel in making early, accurate decisions regarding patient transport and treatment priority.

10. Accurate prediction of stroke for hypertensive patients based on medical big data and machine learning algorithms: Retrospective study.

The goal of the artefact was to use machine learning algorithms and historical electronic medical information to create a ultraprecise stroke prediction model for hypertensive patients. Researchers screened 57,671 out of 250,788 registered hypertension patients using machine learning algorithms on data from the Shenzhen Health Information Big Data Platform. 9,421 of them experienced a stroke within the 3-year follow-up period. They used trend features that were collected from multi-temporal medical data in addition to baseline parameters and previous symptoms to improve predictive performance. The dataset was hierarchy by age and gender for the purpose of balanced sampling, giving 19,953 samples divided into test and training sets in the proportion 7:3.Four models of machine learning were employed in modeling, whose performance was also compared with four conventional risk assessment scales.Four of the tested models, XGBoost algorithm, had an AUC of 0.9220, being greater than that of the other three conventional machine learning approaches. The new model performed better in an independent test set and showed an AUC improvement of 0.17 when compared to two traditional risk scores, the Chinese Multiprovincial Cohort Study and the Framingham Stroke Risk Profile.Subsequent analysis demonstrated the usefulness of multitemporal trend parameters in stroke risk prediction, highlighting their importance in the standardized treatment of hypertensive patients.The research concludes that the established model is an accurate tool for predicting the 3-year risk of stroke in hypertensive patients. Its implementation within electronic health record systems may make more extensive and active stroke risk screening possible, thus improving the effectiveness of early disease prevention and intervention strategies.

III.IDENTIFIED RESEARCH GAP

From the literature review, several key research gaps within the domain of stroke diagnosis using neuroimaging and machine learning have become apparent. These gaps can be addressed by leveraging advanced techniques, enhancing existing frameworks, or exploring interdisciplinary integrations.In this analysis, I will describe the research gaps that have been identified and suggest how to close them, including the hints from the research work.

1. Limited Feature Extraction Diversity

Research Gap: A key drawback seen in many studies is the use of a single CNN model architecture e.g., VGG16 or ResNet for feature extraction. The mono-model method limits the range and depth of learned features, since each model can only extract a subset of spatial and contextual patterns in neuroimages. As a result, the extracted feature set might not have the thorough representation needed to correctly differentiate intricate stroke presentations, which would restrict the model's overall diagnostic accuracy and generalizability.

How the Gap Can Be Filled:

To fill the shortage of insufficient feature representation by standalone CNN models, several deep architectures AlexNet, VGG19, InceptionV3, NASNetLarge, and ShuffleNet are combined to achieve complementary features. The combined features yield more diverse representations, enhancing classification performance and generalization. This ensemble process, as asserted by Saleem et al. [1] and Tursynova et al. [4], accelerates stroke detection by capturing richer spatial and hierarchical patterns from neuroimages, enhancing stronger diagnostic models.

Scope of the Contribution: The contribution greatly advances the accuracy of stroke diagnosis through the application of varying CNN structures for feature extraction. By ensemble of multi-model outputs, it captures hierarchical and complementary features lost by a single model. The approach enhances model robustness, cross- dataset generalizability, and flexibility to deal with multifaceted stroke patterns, enabling more accurate and clinically translatable diagnostic systems in medical imaging.

2. Inadequate Feature Selection Techniques

Research Gap: Most of the existing solutions either do not appreciate the need for optimal feature selection or use elementary dimension reduction methods like Principal Component Analysis (PCA), which can unconsciously remove vital stroke-relevant information. This has an obvious impact on the accuracy and stability of stroke diagnosis models.

How the Gap Can Be Filled:

To Fulfil this requirement, our approach includes Particle Swarm Optimization (PSO) for the best feature selection after deep feature extraction from pre-trained models such as VGG19 and InceptionV3. PSO effectively extracts the most informative features without removing stroke- specific information, improving classification accuracy, thus offering a more effective alternative to traditional practices [9].

Scope of the Contribution: This paper initiates a hybrid DL and optimization-based approach to stroke classification from neuroimages. Its aim is to improve diagnostic accuracy by extracting deep features from pretrained CNNs (such as VGG19, InceptionV3) and determining the most informative subset through Particle Swarm Optimization (PSO). In contrast to traditional methods of feature selection being ignored or oversimplified, this method guarantees stroke- related data preservation. The presented model helps in the creation of more accurate, interpretable, and efficient stroke diagnosis tools.

3. Limited Dataset Usage

Research Gap: Most of the current work depends on small or old stroke neuroimaging datasets, which limits training data diversity and complexity, and as a consequence, generalizability and real-world usability of the given models.

How the Gap Can Be Filled:

To address this, the research utilizes a newer and more heterogeneous dataset [13], with more stroke cases across multiple imaging modalities. This provides improved representation of variability in real-world settings. Coupled with sophisticated feature extraction and PSO-based selection, the proposed method improves model performance and enables wider clinical applicability.

Scope of the Contribution: This work advances stroke diagnosis by leveraging a new and heterogeneous neuroimaging dataset to enhance model generalizability and clinical applicability. Through the combination of deep feature extraction and PSO-based feature selection, the proposed method retains vital diagnostic information and presents a stable, scalable solution over existing models that used limited or obsolete data.

4. Overfitting Due to High Model Complexity

Research Gap: Large deep neural networks with lots of parameters are susceptible to overfitting when trained on small medical datasets since they will grasp the limited training samples down pat instead of learn generalizable patterns ultimately compromising model reliability and performance in real clinical settings.

How the Gap Can Be Filled:

The majority of studies employing deep networks for stroke diagnosis are afflicted with overfitting due to the small size of medical databases, which leads to poor generalizability and fluctuating prediction in practical scenarios [9]. To combat this, our approach encompasses techniques such as data augmentation, transfer learning, and regularization (e.g., dropout or L2 regularization) to head off overfitting and boost the model's conception over unseen data.Also, by employing pretrained models on large, heterogeneous datasets, we take advantage of the strength of transfer learning to fine-tune these models for the smaller stroke datasets, improving performance without overfitting [14].

Scope of the Contribution: This work resolves the overfitting problem in deep networks when used on small medical datasets by integrating data

augmentation, transfer learning, and regularization methods. Through the use of pretrained models and fine-tuning them to stroke-specific data, the proposed method improves model generalization and diagnostic accuracy, withstanding limited data robustly.

5. Poor Handling of Imbalanced Classes

Research Gap: Stroke data tend to have imbalanced class distributions where the majority class (e.g., healthy patients) greatly surpasses the minority class (e.g., stroke patients). This imbalanced class distribution may cause biased models to overestimate the majority class and hence lead to poor minority class detection and impaired diagnostic performance, particularly in actual clinical applications where accurate stroke detection is important.

How the Gap Can Be Filled:

Most of the current stroke classification models are affected by class imbalance, resulting in biased predictions biased towards the majority class and loss of capability in identifying strokes correctly [8]. To address this, our work incorporates sophisticated resampling methods (e.g., SMOTE to oversample the minority class) and cost- sensitive learning to allocate more weights to the minority class during model training. We also use ensemble methods such as Random Forest and XGBoost which are more capable of dealing with class imbalance, resulting in even improved model robustness and diagnostic performance in stroke detection [13].

Scope of the Contribution: This research addresses class imbalance in stroke data sets using the introduction of advanced resampling techniques, cost-sensitive learning, and ensemble techniques. By reducing bias toward the preponderance class, these techniques enhance the model's capacity to detect strokes precisely and provide more reliable diagnostic results even when data sets are unbalanced.

6. Neglect of Real-Time Implementation Feasibility

Research Gap: Research often overlooks the deployment problems of running models in real- world clinical settings, focusing primarily on model performance at training and testing, and neglecting vital considerations such as scalability, interpretability, integration with existing healthcare infrastructure, and real-time performance under clinical constraints. This omission constrains the application of research to usable tools for clinicians, which slows down the widespread use of advanced models in healthcare.

How the Gap Can Be Filled:

Most research in stroke diagnosis is concerned with model accuracy without considering the real- world challenges of deployment in clinical settings, including scalability, interpretability, and smooth integration with current healthcare systems [10].To fill this gap, our approach is focused on model efficiency through the assurance that the models we develop are lean and optimized for real- time processing. The model propose system integration solutions to enable compatibility with healthcare infrastructure and incorporate explainable AI methods for enhancing model interpretability in aid of clinician confidence and decision-making. We also propose designing clinical validation frameworks to enable testing of the robustness of models across a range of real- world settings [15].

Scope of the Contribution: This work addresses the challenge of applying stroke diagnosis models to real clinical cases using model efficiency, system integration, and explainability. Through ensuring scalability, optimizing real-time performance, and integrating explainable AI techniques, the proposed approach enhances the application of stroke diagnosis models in the clinical environment. Clinical validation procedures are also targeted by the study to ensure robust performance across diverse healthcare systems.

IV.CONCLUSION

In this paper, the survey has covered the current state of art of stroke detection using machine learning and neuroimaging techniques, covered major advancements, and characterized significant gaps in existing work. The literature puts a strong emphasis on the pressing need for models that are extremely generalizable on heterogeneous patient groups, can efficiently process high-dimensional neuroimages at minimal computational costs, and can be robust against data sparsity and class imbalance. Moreover, most current methods are plagued by inadequate feature representation, poor feature selection, and insufficient temporal modeling of neuroimage sequences.From an extensive review, this research found a number of promising avenues to overcome these problems. These include multi-model deep feature extraction with CNN ensembles, optimization- based feature selection and advanced temporal classification. In addition, the combination of techniques such as data augmentation, transfer learning, and interpretability frameworks can further improve diagnostic reliability and clinical acceptability. The combination of these methods is promising to significantly improve the robustness, accuracy, and efficiency of stroke classification systems.This paper gives valuable hints on the direction of neuroimage-based diagnostic modeling in the future.Future research needs to extend datasets to increase generalizability, use explainable AI to facilitate clinical decision-making, and integrate multimodal data (e.g., text reports, genomic data) for comprehensive stroke evaluation. Finally, by closing the gaps found here, it is possible to construct the next generation of stroke diagnosis models-models that are not just efficient and accurate but also interpretable, adaptable, and clinically deployable in the field.

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