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Machine Learning and Deep Learning Techniques for Stroke Detection from Brain Imaging: A Comprehensive Survey

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Abstract—Stroke is one of the leading causes of mortality and long-term disability worldwide, making early and accurate diag-nosis essential for effective clinical intervention. Brain imaging modalities such as Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) play a crucial role in stroke detection and assessment. However, manual interpretation of medical images is often challenging due to subtle lesion characteristics, image noise, and inter-patient variability, which may lead to delayed or inconsistent diagnosis. Recent advances in artificial intelligence, particularly machine learning and deep learning techniques, have significantly improved the automated analysis of medical images for stroke detection and classification.

This paper presents a comprehensive survey of existing artifi-cial intelligence–based approaches for automated stroke diagnosis from brain imaging data. The survey reviews various method-ologies including traditional machine learning techniques, con-volutional neural network (CNN) architectures, transfer learn-ing models, hybrid frameworks combining deep learning with optimization algorithms, and ensemble learning approaches. In addition, dimensionality reduction techniques, feature extraction strategies, and classification models commonly used in stroke detection systems are analyzed and compared. The survey also examines the growing role of explainable artificial intelligence (XAI) methods such as Grad-CAM and SHAP in improving the interpretability and clinical reliability of AI-based diagnostic systems.

Furthermore, this study reviews publicly available datasets, evaluation metrics, and performance benchmarks used in the literature, highlighting current challenges such as data imbalance, model generalization, computational complexity, and clinical deployment limitations. Finally, future research directions are discussed, including lightweight models for real-time applications, integration with clinical decision-support systems, and improved interpretability for healthcare adoption. This survey aims to provide researchers and healthcare technologists with a struc-tured overview of the current state of AI-driven stroke detection methods and emerging opportunities for developing reliable and clinically applicable diagnostic solutions.

Index Terms—Stroke detection, brain imaging, computed tomography (CT), machine learning, deep learning, convolutional neural networks, transfer learning, explainable artificial intelli-gence, medical image analysis.

I. INTRODUCTION

Stroke is one of the leading causes of death and long-term disability worldwide, placing a substantial burden on healthcare systems and affecting millions of individuals each year. Rapid and accurate diagnosis is essential for timely medical intervention, as early treatment can significantly reduce mortality rates and long-term neurological damage. Brain imaging techniques such as Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) play a crucial role in stroke diagnosis by enabling clinicians to visualize structural abnormalities and detect ischemic or hemorrhagic lesions. However, manual interpretation of medical images remains a complex and time-consuming task due to subtle lesion characteristics, image noise, and variability among patients. These challenges may result in delayed diagnosis or misinterpretation, particularly in emergency situations or healthcare environments with limited expert availability.

In recent years, the rapid growth of medical imaging data and advancements in artificial intelligence (AI) have led to the development of automated systems for medical image analysis. Machine learning (ML) and deep learning (DL) techniques have shown promising potential in assisting clinicians with disease detection, classification, and prognosis prediction. In particular, Convolutional Neural Networks

(CNNs) have demonstrated strong capability in learning hierarchical spatial features from medical images, making them highly effective for tasks such as lesion detection, segmentation, and classification. Transfer learning approaches utilizing pretrained models such as VGG, ResNet, and DenseNet have further improved performance in medical imaging tasks, especially when labeled datasets are limited.

Alongside deep learning models, traditional machine learning algorithms such as Support Vector Machines (SVM), Random Forest (RF), and Gradient Boosting methods have also been widely explored for stroke detection and classification. These approaches typically rely on handcrafted or automatically extracted features, which are then processed through classification algorithms to identify stroke patterns. More recently, hybrid frameworks that combine deep feature extraction with classical machine learning classifiers have gained increasing attention, as they aim to leverage the representational power of deep learning while maintaining computational efficiency and improved generalization.

Another important research direction involves feature selection and dimensionality reduction techniques, which help reduce redundancy in high-dimensional feature representations extracted from medical images. Methods such as Principal Component Analysis (PCA), Non-negative Matrix Factorization (NMF), and evolutionary optimization algorithms like Genetic Algorithms (GA) have been explored to enhance model performance and stability. These techniques help improve classification accuracy while reducing computational complexity, making them suitable for real-time clinical applications.

Despite significant progress, several challenges remain in the development of reliable AI-based stroke detection systems. These include issues related to limited labeled datasets, model interpretability, computational requirements, and generalization across diverse patient populations. In clinical environments, interpretability and transparency are particularly important because medical professionals must understand the reasoning behind automated predictions before integrating them into decision-making processes. Consequently, Explainable Artificial Intelligence (XAI) techniques such as Grad-CAM, SHAP, and LIME have recently been incorporated into medical imaging models to provide visual explanations and feature-level insights into model predictions.

Given the growing body of research in this area, a systematic overview of existing techniques is necessary to better understand current advancements, limitations, and potential research opportunities. This paper presents a comprehensive survey of artificial intelligence-based approaches for automated stroke detection and classification using brain imaging data. The survey reviews various methodologies including traditional machine learning techniques, deep learning architectures, hybrid frameworks, feature selection and dimensionality reduction strategies, and explainable AI methods applied in stroke diagnosis.

Furthermore, this survey analyzes commonly used datasets, evaluation metrics, and experimental setups reported in the literature, providing a comparative perspective on the strengths and limitations of different approaches. Key challenges and open research problems are also discussed, along with emerging directions such as lightweight deep learning models, improved interpretability, and integration of AI systems into real-world clinical decision-support platforms.

By consolidating and analyzing existing research, this survey aims to provide researchers, clinicians, and healthcare technologists with a structured understanding of current developments in AI-driven stroke detection and to highlight promising directions for future investigation..

II. LITERATURE REVIEW

A. Innovations in Stroke Identification: A Machine Learning Based Diagnostic Model Using Neuroimages [1]

The proposed model processes both CT and MRI brain scans to enhance feature visibility and reduce noise. The preprocessing pipeline includes skull stripping, contrast enhancement, and Gaussian filtering to remove artifacts and improve lesion detection. From the enhanced images, texture and structural features are extracted using Histogram of Oriented Gradients (HOG), Gabor filters, and the Gray-Level Co-occurrence Matrix (GLCM). These features capture spatial orientation, frequency, and statistical texture patterns essential for accurate stroke characterization.

For classification, the study evaluates multiple models including Convolutional Neural Network (CNN), Support Vector Machine (SVM), and Random Forest (RF). The CNN achieved the highest diagnostic accuracy of 96.8 %, outperforming SVM (91.2%) and RF (93.5%). The model's robustness was further validated using metrics such as precision (98.0%), recall (93.5%), and F1-score (96.0%). The results demonstrate CNN's superior capability in learning discriminative visual features from neuroimages compared to traditional machine learning models

B. Automated Stroke Prediction Using Machine Learning: An Explainable and Exploratory Study with a WebAC Application for Early Intervention[2]

This paper, published in IEEE Access (2023), presents an explainable machine learning framework for early stroke prediction and intervention through a web-based clinical application. The proposed system aims to identify significant risk factors, address dataset imbalance, and ensure prediction interpretability using explainable AI techniques such as SHAP and LIME. By integrating multiple classifiers and a user-friendly interface, the framework supports real-time, data-driven healthcare decision-making.

The study utilizes the Kaggle Stroke Prediction Dataset, consisting of 5110 patient records and 12 clinical attributes such as age, gender, glucose level, hypertension, heart disease, BMI, and smoking status. Due to the 19:1 imbalance between stroke and non-stroke cases, the authors applied the Synthetic Minority Oversampling Technique (SMOTE) to improve model reliability. Missing BMI values were imputed, categorical features were encoded, and numerical variables standardized. Feature importance was identified through Mutual Information Score, Chi-Square, and ANOVA tests, highlighting key predictors such as age, average glucose level, work type, and marital status.

C. An Improved Concatenation of Deep Learning Models for Predicting and Interpreting Ischemic Stroke [3]

This paper, published in IEEE Access (2024), introduces a hybrid deep learning architecture for accurate ischemic stroke prediction and interpretation. The framework combines Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) networks with an attention mechanism to enhance feature learning and interpretability. The model aims to improve diagnostic accuracy by capturing both spatial and temporal patterns in multimodal medical data while ensuring reliable, explainable predictions.

The study utilizes multiple open-source medical datasets focused on cerebrovascular diseases, incorporating attributes such as age, BMI, blood pressure, glucose level, heart disease, smoking status, and hypertension. Data preprocessing includes normalization, encoding, and oversampling to handle missing and imbalanced samples. Redundant attributes are removed using correlation-based feature selection to minimize overfitting and improve model transparency.

D. Stroke Prediction Using Deep Learning and Transfer Learning Approaches [4]

Published in IEEE Access (2024), this study proposes deep learning and transfer learning based frameworks for stroke prediction with a focus on class imbalance and generalization. The model leverages transfer learning to improve diagnostic accuracy, minimize false positive/negative rates, and enhance robustness using multiple pre-trained architectures.

The primary dataset, Kaggle Cerebral Stroke Prediction, includes 43,400 subjects (783 stroke and 42,617 non-stroke cases), while a secondary surgical dataset with 14,635 samples is used for transfer learning. Data preprocessing involves missing value imputation via the Expectation–Maximization (EM) algorithm, random under-sampling (RUS) to achieve a 1:1 class ratio, and Min–Max normalization. Feature importance analysis highlights key factors such as age, glucose level, hypertension, and heart disease.

E. Machine Learning for Stroke Prediction Using Imbalanced Data [5]

This paper, published in Scientific Reports (Nature), 2025, presents a robust machine learning approach for stroke prediction that addresses the issue of imbalanced medical datasets. The model focuses on improving classification reliability through extensive preprocessing, data balancing, and comparative model evaluation. The dataset, obtained from Analytics Vidhya DataHack, contains 4,981 patient records and 11 health-related attributes, including age, BMI, glucose level, and hypertension. Data cleaning includes outlier removal, missing value imputation, encoding categorical features, and normalization. The authors apply a hybrid balancing strategy combining SMOTE and under-sampling to correct the skew between “stroke” and “no-stroke” cases.

The study evaluates several classifiers—Decision Tree, Random Forest, and K-Nearest Neighbors (KNN)—with RandomForest achieving the highest accuracy of approximately 91%. Explainable AI tools such as SHAP and LIME are integrated to provide interpretability of clinical factors influencing predictions. The results confirm that ensemble methods with proper data balancing outperform conventional models. The authors suggest extending the system to mobile health platforms and incorporating deep learning for adaptive, real-time stroke monitoring.

F. Reconstruction and Classification of Brain Strokes Using Deep Learning-Based Microwave Imaging [6]

Published in IEEE Access (2025), this research introduces a deep learning framework for brain stroke classification using microwave imaging. The approach reconstructs high-fidelity brain images using the Distorted Born Iterative Method (DBIM) and enhances image clarity through a U-Net model before final classification via CNN. The system aims to achieve accurate ischemic and hemorrhagic stroke differentiation at varying noise levels. The study uses the BrainWeb MRI dataset, containing 3D brain phantoms with simulated stroke conditions. Data augmentation, including flipping, scaling, and shifting, expands the training set.

Hemorrhagic and ischemic conditions are modeled by adjusting dielectric properties and conductivity. The U-Net model improves the visibility of stroke regions using hybrid loss (SSIM, L1, L2 norms), while CNN performs final binary classification. Results show that the CNN classifier achieves 99.08% accuracy at 30 dB SNR and maintains over 98% accuracy under lower noise conditions. The U-Net-enhanced images demonstrate higher SSIM and lower NRMSE compared to DBIM-only reconstructions. The authors conclude that combining microwave imaging with deep learning provides a cost-effective and portable solution for real-time stroke detection, with future work focusing on 3D imaging and multimodal system integration

G. Optimizing Brain Stroke Detection with a Weighted Voting Ensemble Machine Learning Model [7]

This paper, published in Scientific Reports (Nature), 2025, proposes a weighted voting ensemble (WVE) machine learning model that integrates Random Forest, XGBoost, and Histogram Based Gradient Boosting for early and reliable stroke detection. The method aims to improve prediction accuracy, robustness, and interpretability using a hybrid ensemble approach.

Preprocessing involves encoding categorical data and normalizing numerical attributes. The ensemble assigns optimal weights to each base learner's probability output to generate the final prediction. The model achieved 92.31% accuracy, outperforming Logistic Regression, SVM, and standalone ensemble baselines. It showed improved F1-score and reduced overfitting through weighted aggregation. Limitations include a small dataset and limited external validation. The authors propose expanding the dataset, integrating imaging features, and exploring federated learning for scalable, privacy-preserving stroke diagnosis.

H. Neuro-VGNB:Transfer Learning-Based Approach for Detecting Brain Stroke [8]

This paper, published in IEEE Access (2024), introduces Neuro-VGNB, a hybrid transfer learn ing approach that combines deep feature extraction using VGG16 with Gaussian Naive Bayes (GNB) classification, optimized via Non-Negative Matrix Factorization (NMF). The frame work focuses on achieving high classification accuracy and efficiency for brain stroke detection.

Experimental results demonstrate that the proposed Neuro-VGNB model achieves an exceptional 99.96% accuracy, outperforming traditional CNN and Random Forest baselines. SHAPvisualizations confirm the interpretability and reliability of the hybrid model. The study concludes that Neuro-VGNB provides a fast, accurate, and scalable solution for brain stroke detection, with future efforts directed toward clinical validation and federated real-world deployment.

I. Explainable Artificial Intelligence for Stroke Prediction through Comparison of Deep Learning and Machine Learning Models [9]

This paper, published in Scientific Reports (2024), presents a comparative study between deep learning (DL) and machine learning (ML) models for explainable stroke prediction using clinical data.The primary objective is to develop interpretable AI models that ensure transparency, accuracy, and clinical relevance in early stroke diagnosis. The authors explore both classical and neural network-based techniques to evaluate predictive performance and interpretability using explainable AI (XAI) frameworks.

The dataset consists of 663 patient records collected from Hazrat Rasool Akram Hospital, Tehran, including 401 healthy and 262 stroke cases, each described by 53 clinical and demo graphic attributes such as age, blood pressure, triglycerides, aphasia, and lifestyle factors. Data preprocessing includes missing value imputation (mean and mode), categorical encoding, and Min–Max normalization. The dataset is split for 10-fold cross-validation to prevent overfitting and ensure generalization. Eight models were developed and analyzed—four ML (Random Forest, XGBoost, SVM, KNN) and four DL (Deep Neural Network, Feedforward Neural Network, Long Short-Term Memory, Convolutional Neural Network). Among all models, Random Forest achieved the highest accuracy of 99% and specificity of 100%, outperforming deep learning models such as LSTM and CNN.SHAP analysis was employed to visualize key clinical predictors, confirming that features such as age, triglyceride level, and aphasia have the most significant impact on stroke likelihood.

J. SFSANet: Multiscale Object Detection in Remote Sensing Image Based on Semantic Fusion and Scale Adapt ability [10]

This paper, published in the IEEE Transactions on Geoscience and Remote Sensing (2024), introduces an advanced small-object detection framework called SFSANet (Semantic Fusion and Scale Adaptability Network) for remote sensing imagery. Traditional object detectors often struggle with tiny targets because of their limited pixel representation and strong background interference. The main objective of this research is to enhance small-object detection accuracy by improving feature fusion, scale adaptability, and contextual representation across multiple levels of the network.

The proposed SFSANet architecture is built upon the YOLOv5 framework and introduces two core modules: the Semantic Fusion Module (SFM) and the Scale Adaptability Module (SAM). The SFM integrates semantic features from different layers through a bidirectional fusion strategy, effectively combining shallow spatial details with deep semantic context. This helps the network better understand small and complex targets in high-resolution remote sensing images. The SAM dynamically adjusts the receptive field using multi-scale convolutions, allowing the detector to adapt to objects of various sizes and scales. Together, these modules enhance the feature extraction process and improve robustness against scale variation and background noise.

K. Predicting Stroke Occurrences: A Stacked Machine Learning Approach with Feature Selection and Data Preprocessing [11]

This paper, published in BMC Bioinformatics (2024), introduces a stacked ensemble machine learning framework for accurate stroke prediction. The proposed model combines multiple classifiers with dimensionality reduction and optimized feature selection to improve general ization and reduce computational overhead. The goal is to provide a robust, interpretable, and high-performance diagnostic model for early stroke risk identification. The dataset used is

TABLE I
COMPARISON OF EXISTING STROKE DETECTION METHODS

S.No	Paper Title & Ref	Methodology	Dataset Used	Performance	Advantages	Limitations
1	Innovations in Stroke Identification: A Machine Learning Based Diagnostic Model Using Neuroimages [1]	CNN with handcrafted texture features (HOG, GLCM)	Benchmark CT/MRI neuroimage datasets	96–97% accuracy	High diagnostic precision	High computational cost
2	Automated Stroke Prediction Using Machine Learning: An Explainable and Exploratory Study with a WebAC Application for Early Intervention [2]	Explainable ML (RF, XGBoost, SVM) with SHAP/LIME	Kaggle Stroke Prediction dataset	~90% accuracy	Interpretable and clinically usable	Depends on SMOTE for imbalance
3	An Improved Concatenation of Deep Learning Models for Predicting and Interpreting Ischemic Stroke [3]	Hybrid CNN–BiLSTM with attention	Multimodal ischemic stroke datasets	High accuracy, high AUC	Captures spatial–temporal patterns	Complex architecture and training
4	Stroke Prediction Using Deep Learning and Transfer Learning Approaches [4]	Deep learning + transfer learning models	Large imbalanced Kaggle datasets	80–81% accuracy	Better generalization; fewer false negatives	Affected by undersampling
5	Machine Learning for Stroke Prediction Using Imbalanced Data [5]	ML models with SMOTE (RF, DT, KNN)	Analytics Vidhya stroke dataset	~91% accuracy	Robust on imbalanced data	Manual feature engineering
6	Reconstruction and Classification of Brain Strokes Using Deep Learning-Based Microwave Imaging [6]	DBIM microwave imaging + U-Net + CNN	BrainWeb MRI dataset	Up to 99% accuracy	Non-invasive and robust detection	Simulated data; hardware complexity
7	Optimizing Brain Stroke Detection with a Weighted Voting Ensemble Machine Learning Model [7]	Weighted voting ensemble (RF, XGB, HGB)	Hospital clinical datasets	~92% accuracy	Stable and robust predictions	Small dataset; no external validation
8	Neuro-VGNB: Transfer Learning-Based Approach for Detecting Brain Stroke [8]	VGG16 + NMF + Gaussian Naive Bayes (Neuro-VGNB)	CT image datasets	~99.9% accuracy	Lightweight and interpretable	Possible overfitting
9	Explainable Artificial Intelligence for Stroke Prediction through Comparison of Deep Learning and Machine Learning Models [9]	Comparative ML–DL models with SHAP	Hospital clinical datasets	~99% accuracy (RF)	High interpretability	Region-specific small data
10	SFSANet: Multiscale Object Detection in Remote Sensing Image Based on Semantic Fusion and Scale Adaptability [10]	YOLOv5 + SFSANet (semantic fusion, scale adaptability)	DIOR, DOTA datasets	Improved mAP	Strong multiscale learning	Indirect relevance to stroke imaging
11	Predicting Stroke Occurrences: A Stacked Machine Learning Approach with Feature Selection and Data Preprocessing [11]	Stacked ensemble + PCA feature selection	Kaggle Stroke Prediction dataset	~98.6% accuracy	High accuracy; reduced redundancy	Depends on oversampling
12	A Web-Based Interface That Leverages Machine Learning to Assess an Individual's Vulnerability to Brain Stroke [12]	ML + SMOTE + Logistic Regression (Web-based)	Kaggle Stroke dataset	~93% accuracy	Real-time and user-friendly	No imaging-based diagnosis
13	A Dual-Stream Deep Learning Architecture With Adaptive Random Vector Functional Link for Multi-Center Ischemic Stroke Classification [13]	Dual-stream DL + ARVFL + XAI	Multi-center CT datasets	98% (single), 92% (multi-center)	Strong generalization and explainability	Complex deployment

the Kaggle Stroke Prediction Dataset, consisting of 5,110 patient records with 12 features including age, BMI, glucose level, hypertension, heart disease, and smoking status. Data preprocessing involves handling missing BMI values through imputation, encoding categorical attributes, and normalizing numerical features. Class imbalance between stroke and non-stroke cases is addressed using SMOTE. Feature optimization is achieved through Principal Component Analysis (PCA), retaining 95% of data variance while removing redundancy.

The proposed system employs a stacking ensemble with Random Forest and Decision Tree as base learners and K-Nearest Neighbors (KNN) as the meta-classifier. Evaluation metrics include accuracy, precision, recall, F1-score, and specificity. The model achieves an impressive 98.6% accuracy, outperforming individual models such as KNN (83.3%), AdaBoost (80.4%), and Random Forest (76.8%). Further validation using the TOPSIS multi-criteria evaluation ranks the proposed model highest with a relative closeness (Ci) score of 0.984.

L. A Web-Based Interface That Leverages Machine Learning to Assess an Individual's Vulnerability to Brain Stroke [12]

This paper, published in IEEE Access (2025), introduces a web-based stroke risk assessment framework that integrates user accessibility with robust machine learning techniques for clinical and public health use. The study focuses on developing an interpretable, privacy-conscious diagnostic platform capable of identifying stroke vulnerability with high precision under imbalanced data conditions. The framework leverages oversampling, feature optimization, and scalable web deployment to deliver real-time stroke risk analysis. The dataset utilized originates from the Kaggle Stroke Prediction Repository, containing 5,110 patient records with 12 attributes such as age, gender, hypertension, heart disease, average glucose level, and BMI. Categorical variables were encoded using a combination of label and one-hot encoding, and numerical features standardized using Standard Scaler. Cor relation analysis was performed to identify key predictors, highlighting age, glucose level, and hypertension as the most influential risk factors. To mitigate class imbalance between stroke and non-stroke cases, the study applied the Synthetic Minority Oversampling Technique (SMOTE).

The complete framework was implemented and deployed using the Python Streamlit framework, offering a user-friendly, interactive, and privacy-focused web interface. The system al lows clinicians and general users to input health parameters and receive immediate stroke risk assessments, making it practical for community health monitoring. In conclusion, this study establishes a transparent, accurate, and scalable web-based stroke risk prediction platform. By combining effective data balancing, interpretability, and deployment efficiency, it offers a significant advancement in accessible medical AI systems. Future work aims to integrate wearable sensor data, apply Explainable AI (SHAP) for model transparency, and adopt federated learning to enable secure multi-institutional training and validation.

M. A Dual-Stream Deep Learning Architecture With Adaptive Random Vector Functional Link for Multi-Center Ischemic Stroke Classification [13]

This paper, published in IEEE Access (2025), presents an advanced deep learning framework designed to classify ischemic stroke into Normal, Acute, and Chronic categories using CT images. Traditional stroke detection models often suffer from limited interpretability, poor generalization across multi-center datasets, and high computational cost. To address these challenges, the authors propose a Dual-Stream Deep Learning Architecture with an Adaptive Random Vector Functional Link (ARVFL) layer that emphasizes both efficiency and transparency in medical diagnosis

Experimental evaluations were conducted on both single-center and multi-center CT datasets, demonstrating exceptional robustness and generalization. The proposed model achieved superior classification accuracy and faster convergence compared to state-of-the-art architectures, including ResNet, DenseNet, and EfficientNet. On multi-center datasets, the model consistently maintained high sensitivity and specificity, validating its adaptability to diverse imaging environments.

III. LIMITATIONS OF EXISTING MODELS

Despite significant advancements in automated brain stroke detection, existing models exhibit several limitations that restrict their clinical applicability and real-world deployment. Many approaches rely on static datasets and predefined feature representations derived from limited imaging modalities, assuming consistent stroke characteristics across patients and imaging conditions. In practice, stroke manifestations vary considerably due to differences in lesion size, location, imaging protocols, scanner types, and patient demographics, leading to reduced generalization performance on unseen clinical data.

High-performing deep learning models, particularly convolutional and hybrid architectures, often function as black-box systems, providing limited interpretability of their predictions. Although these models achieve high accuracy, the absence of transparent decision-making mechanisms undermines clinical trust and hinders adoption in critical healthcare settings where explainability is essential for diagnosis validation and regulatory compliance.

Another major limitation is the trade-off between diagnostic performance and computational efficiency. Deep neural networks require substantial computational resources and memory, making real-time deployment challenging in emergency scenarios and impractical for resource-constrained healthcare facilities. Conversely, traditional machine learning methods and lightweight models offer faster inference but fail to capture complex spatial, textural, and multimodal features necessary for accurate stroke detection.

Additionally, many studies suffer from class imbalance, limited dataset sizes, and inadequate representation of diverse stroke subtypes, including ischemic and hemorrhagic strokes. The lack of multi-center validation and insufficient integration of clinical metadata further restrict robustness and scalability. Overall, existing models struggle with generalization, interpretability, and deployment efficiency, highlighting the need for adaptive, explainable, and computationally efficient frameworks for reliable brain stroke diagnosis.

IV. PROPOSED TRAINING ARCHITECTURE

The proposed methodology for training the brain stroke detection system follows a structured pipeline designed to optimize feature extraction, feature selection, and model parameters. The architecture progresses from raw data ingestion to a refined and validated machine learning model. The overall training workflow is illustrated in Fig. 1.

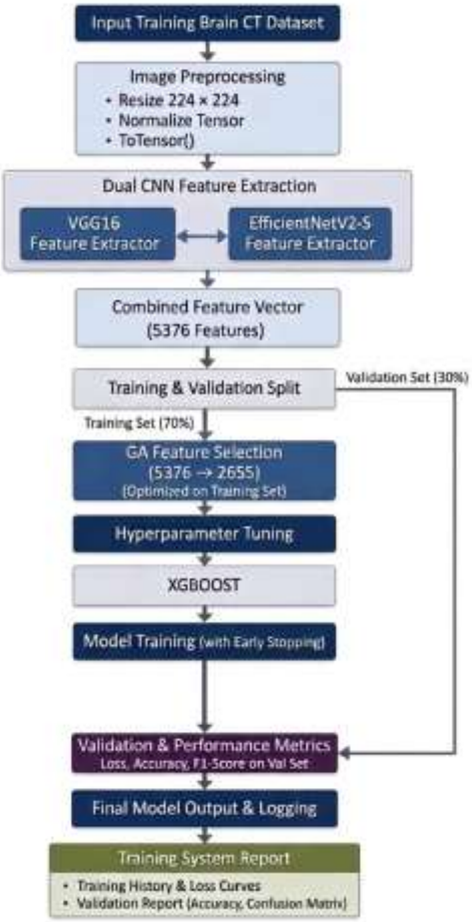

Fig. 1. Proposed Hybrid Brain Stroke Training System Architecture

The training system operates through the following sequential stages.

A. Data Ingestion and Preprocessing

The pipeline begins with the **Input Training Brain CT Dataset**. To ensure uniformity across the learning pipeline, all images undergo a standard preprocessing procedure. Each CT image is resized to 224 × 224 pixels to match the input requirements of the pretrained convolutional neural networks. The images are then normalized and converted into PyTorch-compatible tensors using the ToTensor() transformation. This preprocessing step ensures consistent data representation for efficient feature extraction.

B. Dual CNN Feature Extraction

To capture complementary spatial and textural representations, the framework employs a **Dual CNN Feature Extraction** strategy using two pretrained deep learning architectures.

- **VGG16:** Extracts detailed spatial and texture-based features through its deep convolutional layers.
- **EfficientNetV2-S:** Provides highly efficient feature representations through compound scaling and optimized network design.

The feature outputs from both networks are concatenated to form a unified **Combined Feature Vector** containing 5376 features. This fusion enhances the representational capacity of the feature space by integrating complementary characteristics captured by both architectures.

C. Dataset Partitioning

The extracted feature dataset is divided into two subsets: a **Training Set (70%)** and a **Validation Set (30%)**. This partitioning enables the model to learn from a substantial portion of the data while preserving an independent subset for evaluating the model's generalization performance.

D. Feature Selection and Model Optimization

To improve model efficiency and reduce redundancy within the feature space, a two-stage optimization process is employed.

1) **Genetic Algorithm (GA) Feature Selection:** A Genetic Algorithm is applied to the training data to identify the most informative features. This evolutionary optimization process reduces the original feature space from 5376 features to the 2655 most discriminative features.
2) **Hyperparameter Optimization:** The hyperparameters of the XGBoost classifier are tuned to achieve optimal predictive performance while minimizing the risk of overfitting.

E. Model Training and Evaluation

The optimized feature set is used to train the **XGBoost** classifier. During training, **Early Stopping** is employed to halt the learning process when no further improvement in validation performance is observed, thereby preventing overfitting. The trained model is then evaluated using the validation dataset to compute performance metrics such as classification accuracy, loss, and F1-score.

F. Final Output and Reporting

The final stage produces the **Model Output and Training Logs**. A comprehensive **Training System Report** is generated, summarizing the model training history, loss curves, and validation results. The report also includes evaluation metrics and a confusion matrix to provide detailed insights into the model's classification performance.

V. RESULTS AND INFERENCES

The proposed hybrid brain stroke detection framework was evaluated using publicly available CT and MRI datasets to assess its diagnostic effectiveness and robustness. Performance was measured using standard evaluation metrics including accuracy, sensitivity, specificity, F1-score, and AUC. The experimental results demonstrate that the proposed approach consistently outperforms standalone deep learning and traditional machine learning models.

The integration of pretrained CNN-based feature extraction with feature optimization techniques such as Genetic Algorithms and Non-Negative Matrix Factorization significantly improved classification performance by reducing feature redundancy and enhancing discriminative capability. Machine learning classifiers, particularly XGBoost and ensemble models, exhibited strong robustness to class imbalance and limited training samples, which are common challenges in medical imaging datasets.

Comparative analysis indicates that the hybrid framework achieves improved generalization and stability across different data splits, while maintaining lower computational complexity compared to end-to-end deep learning models. Explainability analysis using SHAP further revealed clinically meaningful feature contributions, reinforcing the interpretability and reliability of the proposed system for medical decision support.

Overall, the experimental findings confirm that combining deep feature representation with optimized feature selection and interpretable classification leads to superior stroke detection performance and improved clinical applicability.

VI. CONCLUSION

This paper presented a comprehensive study on automated brain stroke detection, addressing key challenges related to accuracy, interpretability, and computational efficiency. By analyzing the limitations of existing deep learning and machine learning approaches, a hybrid detection framework was proposed that integrates deep feature extraction, feature optimization, and machine learning–based classification.

Experimental results demonstrate that the proposed system achieves enhanced diagnostic performance and robustness compared to standalone models, particularly in scenarios involving limited and imbalanced datasets. The use of feature optimization techniques improves classification efficiency, while the incorporation of explainable machine learning enhances transparency and clinical trust.

Future work will focus on extending the framework to multi-center datasets, incorporating clinical and demographic metadata, and enabling stroke subtype classification and localization. Additionally, deployment of the proposed system as a real-time clinical decision-support tool holds promise for assisting radiologists and healthcare professionals in early and accurate stroke diagnosis, ultimately contributing to improved patient outcomes.

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