Explainable Stroke Detection using Transfer Learning and Stacking Technique

[1] Amrita Ticku; [2]Anu Rathee; [3] Dhruv Mathur; [4] Deepika Yadav;
[5] Ayush Srivastav
[1, 3, 4] Department of Computer science and Engineering
[2,5] Department of Information and Technology
[1, 3, 4] Bharati Vidyapeeth's College of Engineering, New Delhi, India
[2] Maharaja Agrasen Institute of Technology, New Delhi, India

Corresponding Author: Amrita Ticku

Abstract: Stroke stays among the world's foremost trigger of mortality and disability by annually affecting numerous people with severe medical outcomes. Medical diagnostics requires immediate correct stroke detection because delayed or incorrect stroke diagnosis can lead to severe neurological disabilities or death. In clinical environments, beyond achieving high diagnostic precision, it is imperative that models offer interpretability to foster clinician trust, support informed decision-making, and uphold accountability in AI-assisted healthcare interventions. Therefore, AI-driven stroke detection systems must balance predictive performance with transparency to ensure safe and reliable deployment. This study proposes an Explainable Stacked System for Stroke Detection (EXS3D), that used a Stacking Ensemble technique and transfer learning with multiple deep learning models (Res Net, Efficient Net, Dense Net) as base classifiers, whose outputs were combined through a meta-level Logistic Regression model. To enhance transparency, the system employed Grad-CAM for visual explainability of image-based features in base models, and SHAP and LIME frameworks to interpret the decision-making of the final meta model. The EXS3D system achieved an accuracy of 97.37%, with the meta-model outperforming individual base models in predictive performance. EXS3D exemplifies how explainable AI can be seamlessly integrated into ensemble learning for high-stakes domains like stroke detection.
Keywords: Deep Learning, Stacking Ensemble, CNN, Transfer Learning, XAI

1. Introduction

A stroke is a serious cerebrovascular disorder that develops when blood stops flowing to a particular region of the brain depriving brain cells to receive oxygen and essential nutrients. This has the potential to cause brain cells to start dying posing a high death risk while the survivors can experience long lasting symptoms like confusion, paralysis, dizziness, etc. affecting mobility, speech, cognition, and emotional well-being [1].

Basically, strokes fall into two major types: one is Ischemic stroke and the other is Hemorrhagic stroke. An Ischemic Stroke happens due to the obstruction of the blood vessels supplying blood to the brain and constitutes 87% of the total stroke incidences [2]. Ischemic stroke can result from arteriosclerosis, thrombus formation, embolism, arterial dissection, or systemic hypoperfusion, all causing diminished cerebral blood flow and subsequent ischemia [3]. Ischemic stroke disrupts autonomic reflexes, leading to impaired cardiovascular regulation, abnormal heart rate, and blood pressure fluctuations, thereby affecting overall physiological stability [4]. Hemorrhagic Stroke or Cerebral Hemorrhage is a result of bursting of a brain blood vessel that leads to blood accumulation and compression of the surrounding brain tissue [5]. Though Hemorrhagic Stroke accounts for only about 13% of the stroke cases but can cause serious damage to the brain and can also be fatal [5][6]. Most commonly it is caused by high blood pressure [6].

Stroke acts as a global cause of both premature death and long-lasting disability. Worldwide, one in every four individuals over 25 years of age is likely to experience a stroke during their lifetime [7]. As per World Health Organization, every year, around 15 million people are affected by the stroke globally, one-third among them dies while one third people face permanent disabilities, creating significant challenges for their families and communities [1]. The need of the hour is to detect the brain stroke at the earliest to avoid any serious complications due to the stroke.

AI and deep learning are transforming stroke detection by enabling faster, more accurate, and automated CT scan analysis compared to traditional manual methods. While radiologists rely on time-consuming and subjective inspection, CNN-based deep learning models can swiftly detect subtle patterns across thousands of scans [8]. These models enhance diagnostic speed and accuracy, supporting data-driven decisions. Additionally, Explainable AI (XAI) improves transparency, fostering trust in AI-driven stroke predictions [9].

This study proposes an Explainable Stacked System for Stroke Detection (EXS3D), which applies Stacking Ensemble Learning with transfer learning, combining softmax outputs from multiple pre-trained models as meta-learner inputs to improve classification and generalization. The dataset comprising 2,501 CT images [10] is used to train deep learning models for stroke classification. To enhance transparency and clinical interpretability, Explainable AI (XAI) techniques are applied to interpret model decisions.

This document features the following structure: Section 2 explores related work regarding AI-based stroke detection methods and the proposed methodology. Section 3discusses the evaluation results and the role of XAI techniques in enhancing model transparency. Section 4 concludes with key findings and future directions for AI-driven stroke detection.

2. Materials and methods

2.1 Related works

D. -H. Shih et al. [11] developed a stroke forecasting system using stacking approach in machine learning combined with Principal Component Analysis and Factor Analysis for feature extraction. The model achieved 92.55% accuracy, demonstrating the effectiveness of dimensionality reduction techniques. However, the study highlighted challenges related to high-dimensional features, which increase computational complexity and hinder learning efficiency.

M. A. Saleem et al. [12] developed an enhanced deep learning detection model for ischemic strokes using combination of CNNs and LSTM networks. Higher interpretability of predictions became possible through the Explainable AI integration with the SHAP technique. The model delivered 95.9% accuracy despite working with a dataset problemized by its high level of imbalance and noise which might reduce model generalizability.

S. Sahriar et al. [13] explored the deep learning and transfer learning application for stroke detection. By utilizing pretrained deep networks, the study achieved 80.5% accuracy with a Transfer Learning Deep Neural Network (TL-DNN) model. However, further optimizations were needed to enhance accuracy and reduce dependency on labeled data.

M. J. Ferdous and R. Shahriyar [14] proposed an ensemble CNN model (ENSNET) for stroke prediction, integrating pretrained networks such as InceptionV3, MobileNetV2, and Xception. ENSNET achieved a high accuracy of 98.86%, surpassing individual models. However, test evaluations revealed overfitting, suggesting the need for regularization to enhance generalization.

R. Qasrawi et al. [15] described a combined deep learning ensemble model, integrating a Stroke Precision Enhancement Model (SPEM) with intelligent lesion detection techniques. Their approach significantly improved stroke classification accuracy from 0.876 to 0.982 across stroke stages. However, the study emphasized the need for larger dataset validation and improved integration into clinical workflows.

D. Ushasree et al. [16] created an Enhanced Stroke Prediction System using Stacking Methodology (ESPESM) with Random Forest as the meta-classifier. Their stacking model outperformed solo models, achieving a 98% accuracy. However, the model training procedure used a restricted data collection., which may restrict its real-world applicability.

A. Srinivas and J. P. Mosiganti et al. [17] developed an ensemble machine learning model which used soft-voting for detecting strokes. Their proposed system achieved 96.88% accuracy but lacked external validation on real-world clinical datasets, limiting its potential for real-world applications.

J. Yu et al. [18] developed stroke prediction technology based on artificial intelligence as they analyzed ECG and PPG bio-signals combined with deep learning techniques (CNN + LSTM). Their approach achieved 99.15% accuracy, demonstrating the effectiveness of time-series deep learning models. However, the absence of external validation datasets raised concerns about the model's generalization to unseen patient data.

Y.-A. Choi et al. [19] created stroke detection technology using deep learning methods which included LSTM networks together with CNN-LSTM and Bidirectional LSTM networks. The proposed model delivered 94% accuracy together with 6% false positive rate and 5.7% false negative rate. However, the study noted that MRI/CT imaging is expensive and time-consuming, making real-time deployment challenging.

Various detection methods incorporating machine learning and deep learning led to promising results in stroke diagnosis according to existing research. The system needs a robust stroke detection tool with explanatory capabilities and balanced performance because it faces limitations from insufficient validation and interpretability issues along with high complexity. The EXS3D model solves such problems through an ensemble framework combination with explainable AI methods that utilizes multiple diverse models to increase predictive accuracy while generating understandable results for clinical assessment.

2.2 Methodology

Figure 1 illustrates the stages involved in model development.

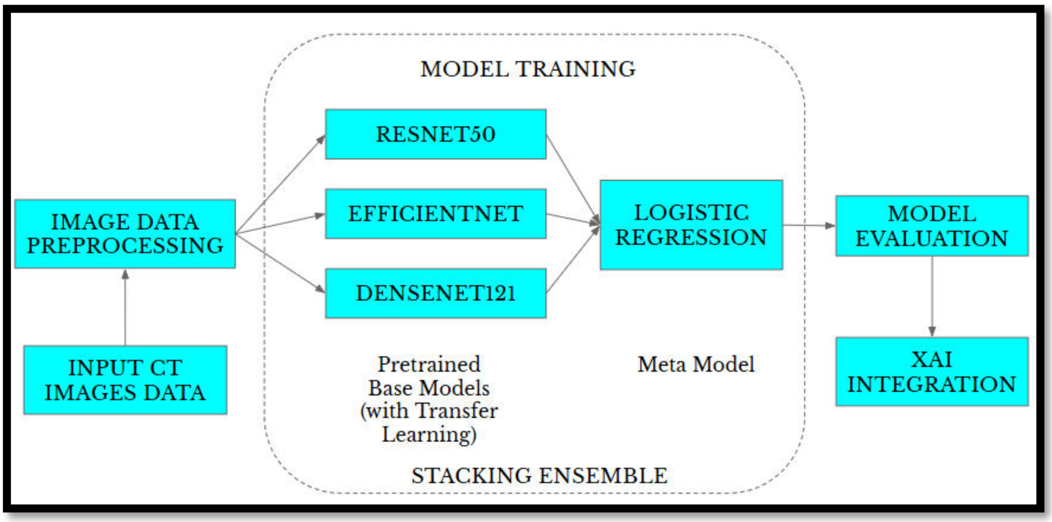


Figure 1: Stages in the proposed model

2.2.1 Experimental Setup

The computational configurations and software utilities employed in the formulation of the proposed framework are delineated in Table 1.

Table 1Resources used in the project.

Resource	Details
CPU	12th Gen Intel(R) Core(TM) i5-12500H 2.50 GHz
RAM	16 GB
GPU	NVIDIA GEFORCE RTX 3050 Laptop
Software Tools	Jupyter Notebook, Visual Studio Code

2.2.2 Dataset Description

The dataset [10] used for stroke detection consisted of 2,501 CT images, with 950 stroke images and 1,551 normal images each measuring 650 × 650 pixels at 96 DPI resolution. These images were sourced from Kaggle, a large repository for publicly available datasets.

2.2.3 Data Preprocessing

To ensure effective training and evaluation, the dataset was stratified by class—1,551 normal and 950 stroke CT images. Due to the inherent imbalance between classes in the dataset, where non-stroke cases significantly outnumbered stroke cases, under sampling of the majority class was employed to achieve a balanced distribution of samples across both classes. Random under sampling was chosen to prevent the model from becoming biased toward the dominant class and to ensure equitable learning of minority class patterns. Alternative resampling strategies, such as SMOTE and weighted loss adjustments, were explored; however, random under sampling demonstrated stable convergence and superior generalization in our experimental setup. This balanced dataset was evenly distributed into training set, validation set, and testing set as detailed in Table 2. This approach mitigated class imbalance, reduced model bias, and supported reliable pattern learning. The subsets were organized into dedicated directories (train, val and test) compatible with Py Torch's Image Folder for streamlined data loading and label handling.

Before being fed into the model, all CT images originally grayscale with dimensions 650×650 at 96 DPI were reduced to 224×224 pixels and then converted into three channel RGB format. To enhance model robustness and minimize over fitting, the training data was augmented using a set of transformations: horizontal flipping with a probability of 0.5, random brightness and contrast adjustments with a probability of

0.2, and random rotations within a ±20-degree range. These augmentations simulated real-world variations in medical imaging.

Following augmentation, all images in the training and validation sets underwent normalization through the application of Image Net statistical values including a mean of [0.485, 0.456, 0.406] and standard deviation of [0.229, 0.224, 0.225] to ensure compatibility with pre-trained convolutional neural networks. By performing class balancing prior to training through random under sampling, the dataset provided an equal number of examples for each class—950 normal and 950 stroke images—facilitating unbiased learning and consistent evaluation across all phases of the training pipeline.

Table 2 Balanced Dataset Distribution across Splits

Image Set	Stroke	Normal	Total	Split Percentage
Train Set	143	143	286	70%
Val Set	712	712	1424	15%
Test Set	95	95	190	15%

2.2.4 Proposed Model Architecture

The proposed EXS3D model employed Stacking Ensemble Learning to enhance classification accuracy and generalization by integrating multiple deep learning architectures. Unlike single-model approaches, stacking captured diverse feature representations, mitigating bias and over fitting. The framework comprised base models that extract spatial and textural features, and a meta-learner that refined predictions by learning optimal combinations of the base models' soft max outputs.

The EXS3D model utilized transfer learning by adapting pre-trained convolutional neural networks(CNNs) for extraction of features for stroke detection. This approach enhanced performance and reduced training time, particularly in data-limited scenarios, by leveraging learned visual representations from large-scale datasets.

- **Res Net-50:** ResNet50 operates as a 50-layer deep CNN which solves degradation problems by incorporating skip connections into residual learning structures to help gradient propagation. The design of this architecture helps efficiently learn difficult features which makes it an essential framework for many computer vision projects because of performance excellence and generality.

- **Dense Net-121:** DenseNet-121 operates as a densely connected CNN sending information from every preceding layer to each subsequent layer which allows extended feature reuse and gradient transfer optimization. Stroke detection benefits from DenseNet-121 because its short parametric structure enables learning from small medical image datasets as it improves detection accuracy and generality.

- **Efficient Net-Bo:** EfficientNet-Bo is a lightweight CNN leveraging compound scaling to balance depth, width, and resolution for optimal accuracy and efficiency. Its low computational cost and high performance make it ideal for real-time stroke detection, enabling fast, precise inference in resource-constrained clinical settings.

Following model is used as the meta model

Logistic Regression: Logistic Regression functions as an essential binary classification technique which creates predictions through linear boundaries combined with sigmoid functions. Logistic Regression serves as a meta-model in stacking ensemble to combine diverse base learner predictions for making the final decision that achieves better accuracy and robustness.

2.2.5 XAI Integration

Explainable Artificial Intelligence (XAI) comprises techniques that enhance the transparency and interpretability of AI model decisions, fostering trust and accountability in critical fields like healthcare. In this study, XAI is integrated into the EXS3D framework to provide visual insights into model predictions, ensuring that decisions are based on medically relevant regions of brain CT scans—an essential requirement for reliable stroke diagnosis.

Grad-CAM served as our tool to add interpretability to base deep learning models by showing which image areas drive the prediction outcome. The technique generated maps for each CT image class to ensure the model examines meaningful anatomical areas. This method assists clinicians in developing confidence through validation of how the deep learning model interacts with CT images to prevent dependency on incorrect correlations.

The interpretation of the final meta-model (Logistic Regression) used SHAP and LIME as model-agnostic XAI techniques. LIME provided local explanations through approximation of individual instances while SHAP distributes values to features using game theory. These interpretive tools enhance worldwide along with local interpretability capabilities which improves transparency as well as trust in the ensemble model's operations of making decisions.

3. Results and Discussion

The results of our model are shown in this part along with a comparison with base models. Our work concentrated on utilising Stacking Ensemble Method for creating a reliable model for early Stroke detection. Four CNN pre-trained models were served as the base models whose outputs were fed into Logistic Regression Classifier serving as meta model.

3.1. Evaluation Metrics

For assessing the performance of our model, Multiple metrics formed the basis of our model evaluation:

- Accuracy: It is the metric that provides us with a holistic evaluation of the accuracy rate of our model.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \tag{1}$$

- Precision: It indicates the frequency with which the model correctly predicts a positive case.

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{2}$$

- Recall: It is concerned with identifying all relevant positive instances, ensuring that no true positives are missed, even if it means occasionally including false positives.

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{3}$$

- F1-Score: The F1-score combines precision and recall through harmonic mean calculations in order to determine a balanced evaluation offering a fair assessment of model performance thus working well for unbalanced classes.

$$\text{F1} - \text{Score} = \frac{2*\text{Precision}*\text{Recall}}{\text{Precision+Recall}} \tag{4}$$

- AUC-Score: The AUC (Area under the Curve) score represents model's discrimination capability among the classes throughout multiple threshold levels, with higher values indicating better discriminatory performance.

The proposed EXS3D demonstrates strong classification performance, achieving 97.37% accuracy, 98.91% precision, 95.79% recall value and F1-score of 97.33%. These metrics indicate a balanced and reliable model, effectively minimizing false positives and false negatives. The experimental outcomes find additional support from Figure 2 which shows the confusion matrix.

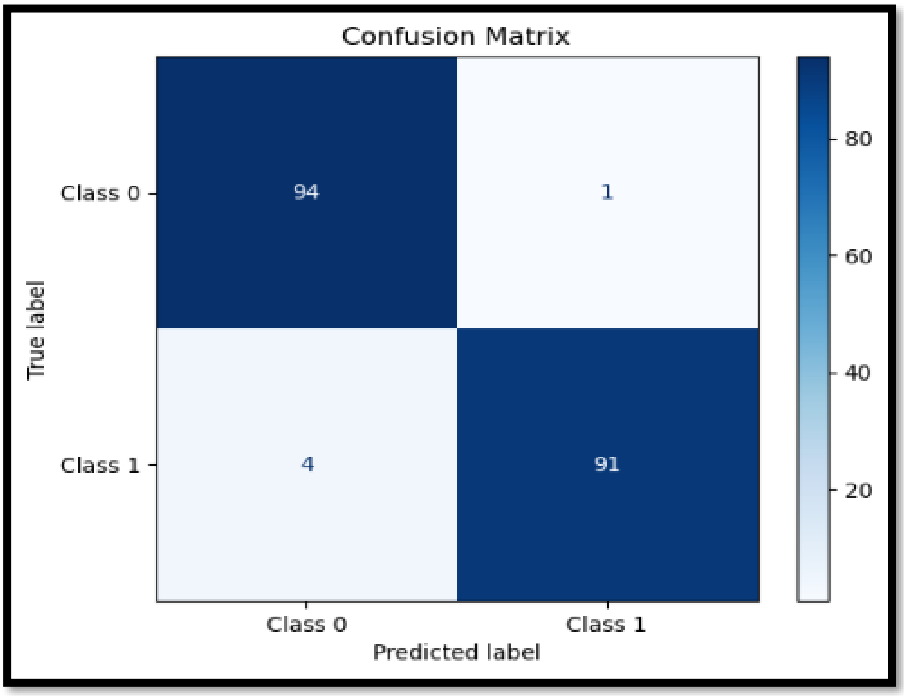


Figure2 Confusion Matrix

3.2 Receiver Operating Characteristic (ROC) Curve Analysis

The AUC-ROC curve shows a trade-off zone between true positives and false positives during model discriminative ability assessment. As shown in Figure 3, meta model achieves an excellent AUC score of 0.996, indicating near-perfect classification performance. This underscores the EXS3D model's robustness and reliability in accurately distinguishing between Stroke and Normal cases.

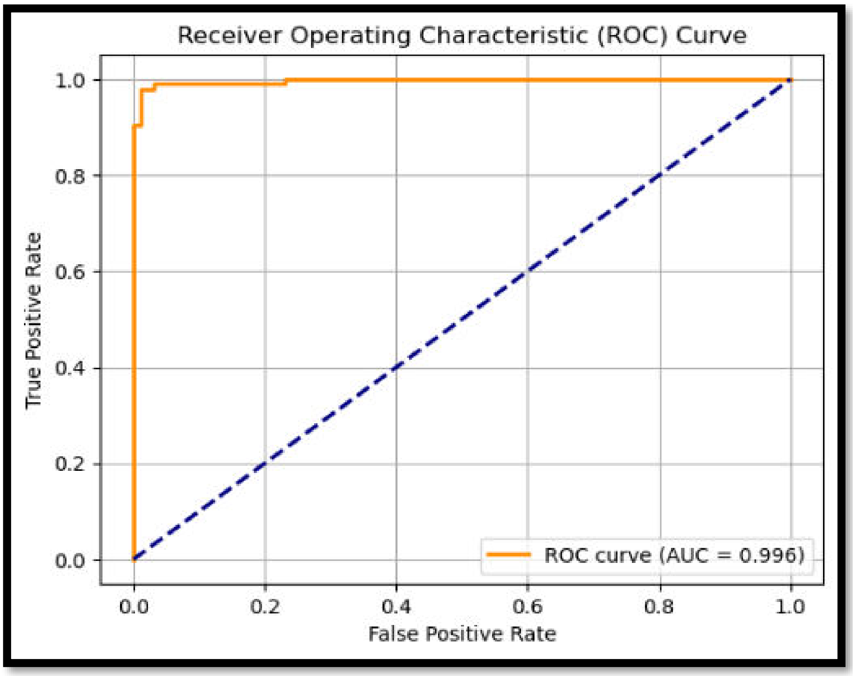


Figure 3 AUC-ROC Curve

3.3 Precision-Recall Trade-off

With class imbalance addressed through a Random Under sampling, the Precision-Recall (PR) curve is analyzed to assess performance on the underrepresented class. As shown in Figure 4, the model got a high average precision (AP) of 0.997, maintaining strong precision across various recall values. The position of the curve close to the top-right corner shows the model performs effective positive stroke detection along with low numbers of incorrect detections.

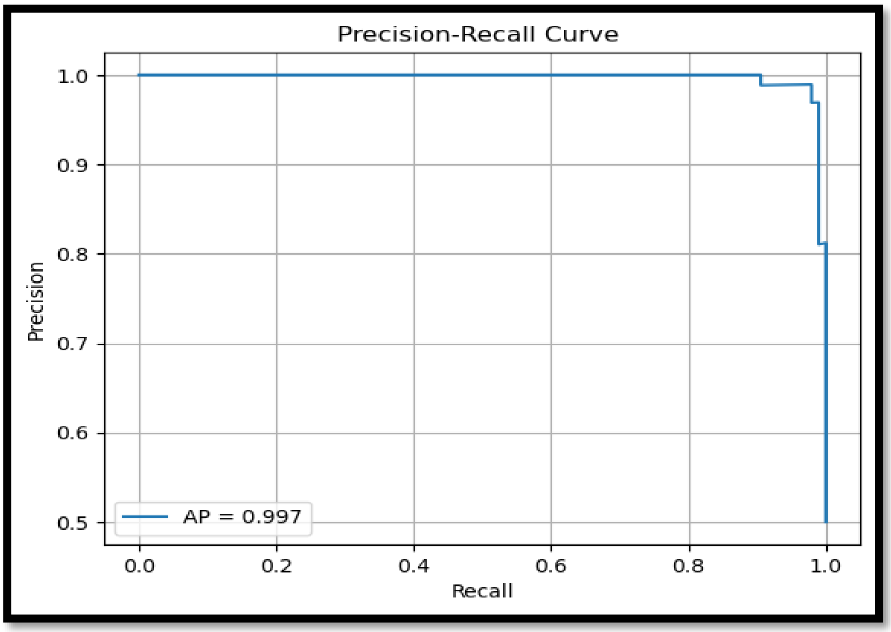


Figure 4 Precision-Recall Curve (PR Curve)

3.4 Comparative Evaluation of Classifiers

To verify the efficiency of the proposed EXS3D model, its performance was benchmarked against its underlying base classifiers. Table 3 illustrates a comparative analysis of individual base models Resnet50, Efficient Net, DenseNet121 along with the final stacked ensemble architecture, i.e., the EXS3D model, evaluated across multiple performance metrics.

As presented in Table 3, the EXS3D model consistently outperforms individual base classifiers across all major evaluation metrics Accuracy, Precision, Recall, and F1-score. The EXS3D model achieved the highest value in Accuracy (97.37%) and F1-score (97.00%), reflecting superior and balanced performance. Although ResNet attains perfect Precision (100%), its low Recall (78.00%) indicates missed true positives. EXS3D, in contrast, maintains high Precision (99.00%) and Recall (95.00%). While EfficientNet and DenseNet exhibit strong Recall (95.00% and 97.00%), they fall short in Accuracy and F1-score. These results highlight the robustness of EXS3D's ensemble strategy, effectively leveraging base model strengths while compensating for their limitations. The performance trend is visually supported by the bar plot in Figure 5.

The AUC-ROC analysis (Figure 6) further underscores the excellent performance of the EXS3D model. Possessing the highest AUC value of 0.996 (near 1.0), EXS3D demonstrates strong class discrimination and an optimal sensitivity-specificity balance. While EfficientNet and DenseNet also perform well, their AUC margins are narrower, indicating reduced confidence in borderline classifications. ResNet, though precise, shows the lowest AUC, reflecting limited consistency in detecting positive cases. These results affirm the advantage of ensemble learning in EXS3D for achieving more reliable class separation.

In contrast, the stacking model outperformed all individual base models by achieving an accuracy of 84.04%, with precision of 0.83, recall value of 0.75, and F1-score of 0.79. The notable improvement in recall underscores the model's enhanced ability in identifying stroke cases correctly. By combining multiple models, the stacking approach improved generalization, reduced bias, and boosted overall classification performance, demonstrating that ensemble learning is more effective for stroke detection than single deep learning models.

Table 3: Comparison between the base models as well as the EXS3D model

Model Name	Accuracy	Precision	Recall	F1-score
Resnet	88.95%	1.0	0.78	0.88
Dense net	92.63%	0.89	0.97	0.93
Efficient Net	96.32%	0.98	0.95	0.96
EXS3D Model	97.37%	0.99	0.95	0.97

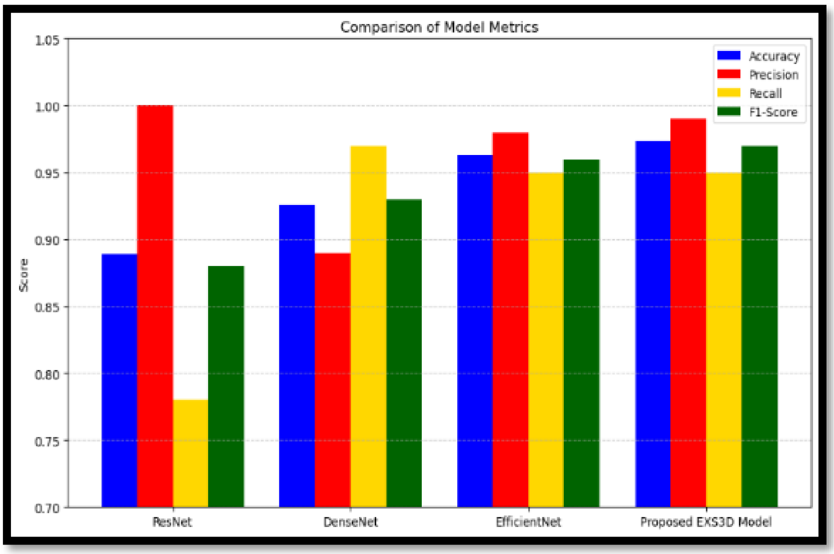


Figure 5 Bar Plot for Comparison between base models and EXS3D model

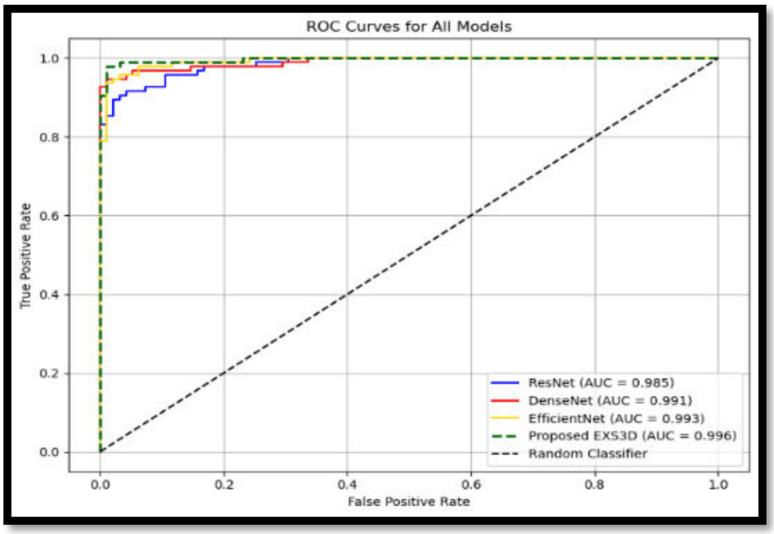
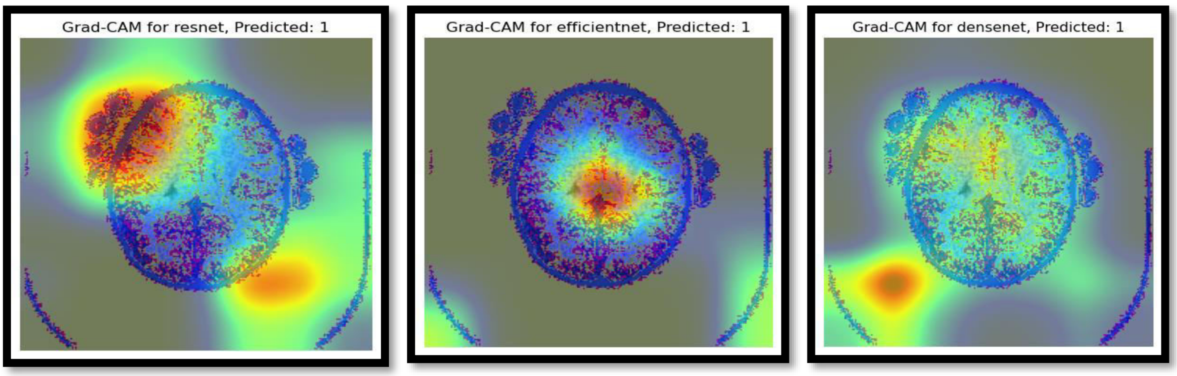


Figure 6 AUC ROC Curves for base models and EXS3D Model

3.5 Explainability Analysis using XAI

To further enhance the transparency and trustworthiness of the proposed EXS3D framework, various explainable AI (XAI) techniques were employed on base models and the meta model.

Grad-CAM was used in visualizing the decision-making of base models—Res Net, Efficient Net, and Dense Net—by generating class-specific heat maps from individual brain CT scans. This technique highlights regions influencing stroke predictions by utilizing gradients from the final convolutional layers. As shown in Figure 7, Res Net (Figure 7(a)) emphasizes the left region, Efficient Net (Figure 7(b)) focuses centrally, and Dense Net (Figure 7(c)) attends to relevant but dispersed areas. These heat maps confirm the models' attention to clinically significant regions, supporting the stacking model's interpretability and reliability.



(a) (b) (c)

Figure 7 Grad-CAM visualizations for an instance using Base Models

SHAP analysis helped reveal the world-wide impact of base models upon the logistic regression final prediction. According to SHAP summary analysis results in Figure 8. Dense Net demonstrates the maximum average effect on model outputs which Efficient Net and Res Net follow closely behind. Figure 9 represents the SHAP waterfall plot that depicts a single diagnosis where all three component models contribute positively to classify the patient as having a stroke. Dense Net attributes +1.62 to the output while Efficient Net assigns +1.42 and Res Net gives +1.23 according to SHAP values. The explanations of ensemble decision-making validate its process and demonstrate which base models provide the most critical information.

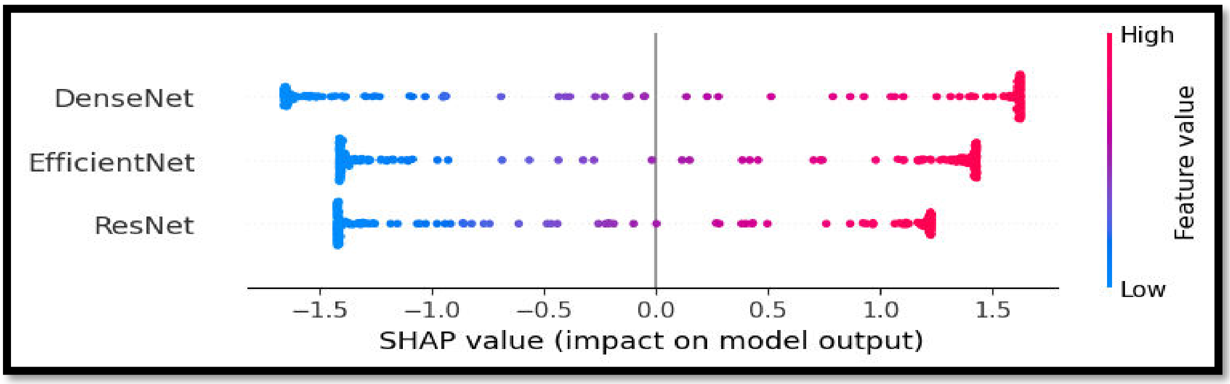


Figure 8 SHAP Summary Plot

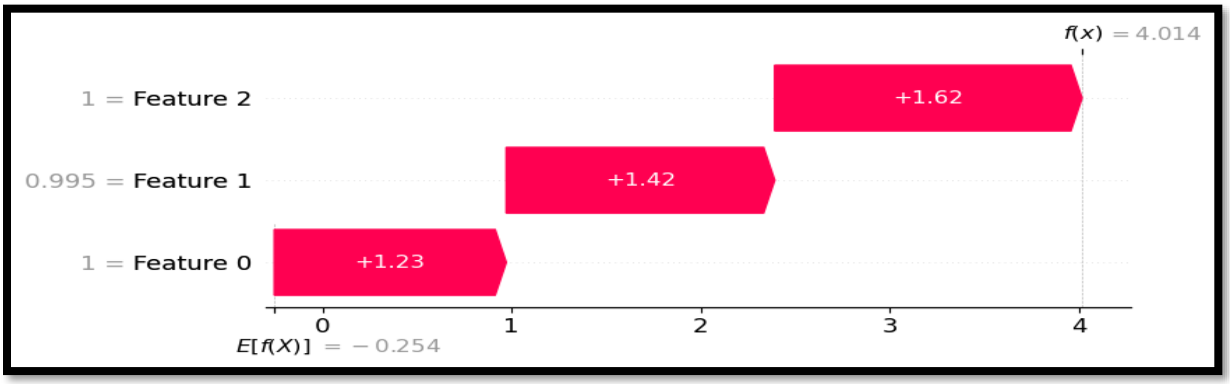


Figure 9 SHAP Waterfall Plot

The meta-classifier received individual explanations from LIME regarding stroke and non-stroke predictions on specific instances. All base models with high outputs at 0.98, 0.99, and 0.95 for Dense Net and Res Net and Efficient Net influenced positively the meta-classifier decision (Figure 10). The models produced low output values to indicate stroke is unlikely in negative case scenarios (Figure 11). The LIME model successfully demonstrates base model contributions which improves system transparency as well as healthcare practitioners' trust in the system during clinical applications.

The integration of XAI techniques enhances the interpretability of our stroke detection model. These visual and feature-based explanations confirm that the models rely on clinically significant cues for decision-making. This not only builds confidence in the model's predictions but also ensures transparency for medical practitioners. Overall, XAI adds a crucial layer of trust, making the system more reliable and human-interpretable.

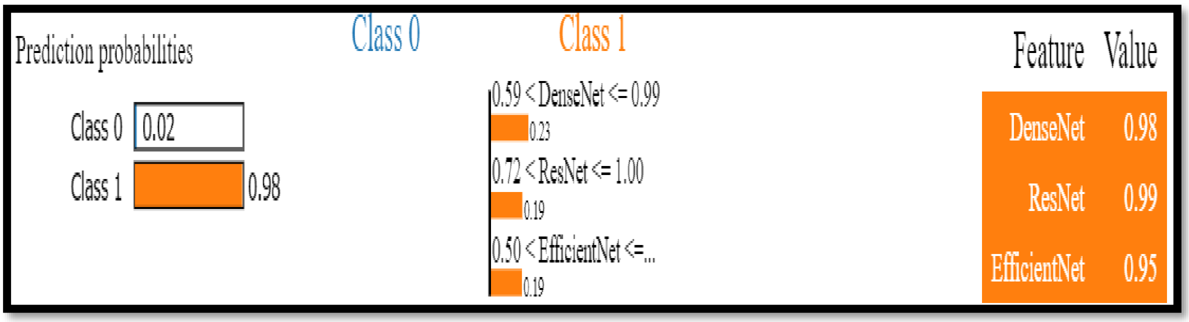


Figure 10 LIME Visualization for Positive Stroke Prediction

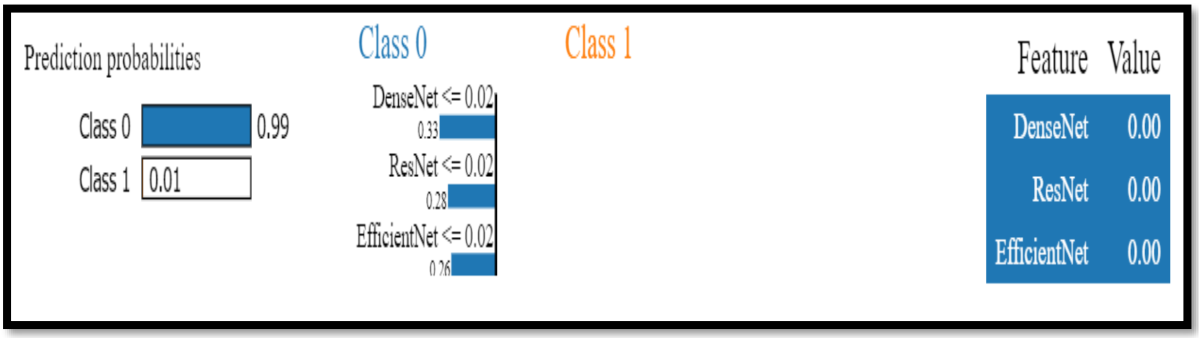


Figure 11 LIME Visualization for Negative Stroke(Normal Case) Prediction

4. Conclusion

This research creates a stroke diagnostic system which combines deep models with transfer learning and explains the process using XAI techniques to analyze brain CT images to detect stroke conditions. A combination of Res Net, Dense Net and Efficient Net as base models and logistic regression as meta-model reached an accuracy of 97.37 in the proposed EXS3D framework. XAI tools Grad-CAM and SHAP and LIME generated understandable visual and feature-level analyses through medical-relevant region identification which led to effective stroke detection patterns.

Our findings highlight the critical role of explain ability in deep learning for healthcare. XAI integration can enhance transparency and support clinical validation by revealing decision-making processes. Furthermore, the ensemble approach improved classification performance and mitigated over fitting, making the system a robust and reliable solution for automated stroke detection.

Despite the promising performance of the proposed EXS3D model, certain limitations should be acknowledged. The dataset used in this study was relatively small in size, and the employment of under sampling technique may have resulted in the loss of potentially valuable information from the majority class (normal class). Additionally, the model has not yet undergone any clinical validation on real-world stroke data, which is crucial for assessing its diagnostic reliability and practical applicability.

Future research will focus on addressing these limitations by incorporating larger, more diverse datasets and collaborating with clinical experts to evaluate the framework on real-world MRI and CT datasets, enabling assessment of its diagnostic reliability and integration into hospital decision-support systems.The addition of transformer-based vision models represents a potential future research objective for increasing data set generalization. Implementing AI models in practice in healthcare institutions can facilitate quick stroke recognition and assist in an interactive decision-making system, which will offer clinicians practical information that will increase diagnostic accuracy.

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