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Stroke Disease and its Types Prediction using Images

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Abstract
Stroke, a leading cause of long-term disability and mortality worldwide, arises from acute cerebrovascular events that disrupt cerebral blood flow. This neurological disorder necessitates rapid diagnostic imaging and timely intervention to minimize irreversible brain damage and improve patient outcomes.The disease prediction requires a structured image-based analysis approach that can identify the presence of stroke and provide further interpretation of its progression. This study presents a hierarchical deep learning framework for stroke disease prediction from brain scan images. The proposed system performs prediction in three sequential levels. First, a binary Convolutional Neural Network (CNN) model classifies the input brain scan image as Normal or Stroke. If stroke-related features are detected, the image is passed to next CNN model for classification into Stage 1, Stage 2, or Stage 3. The system further estimates severity by extracting feature maps from the stage classification CNN and applying K-Means clustering to the extracted deep features. The clustered feature score is combined with stage-based risk priors and prediction confidence to categorize the severity level as Low, Medium, or High. This framework contributes a multi-level stroke screening pipeline by integrating stroke detection, stage classification, and feature-based risk estimation within a single deployed system.
Keywords: *Stroke Disease, Prediction, Deep Learning, Convolutional Neural Network, Stage Classification, Severity Estimation, K-Means Clustering.*

1. Introduction

Taking early and accurate diagnosis essential for effective treatment and improved patient outcomes. Brain imaging techniques such as Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) are widely used to identify stroke-related abnormalities. However, manual interpretation of these images is time-consuming and depends heavily on the expertise of radiologists. Recent advances in deep learning have significantly improved the automatic analysis of medical images by enabling models to learn complex spatial features directly from brain scans. In particular, Convolutional Neural Networks (CNNs) have demonstrated strong performance in image classification and disease detection tasks. Several researchers have explored deep learning techniques for stroke analysis using brain imaging. Cui et al. [1] presented a comprehensive review of deep learning applications in ischemic stroke imaging, highlighting the use of CNN-based models for diagnosis, lesionsegmentation, treatment planning, and outcome prediction. Their review emphasized the effectiveness of deep learning in medical image analysis while identifying the need for more integrated frameworks capable of performing multiple stroke-related tasks within a single system. Ozaltin et al. [2] introduced the OzNet CNN architecture for binary classification of brain CT images into Normal and Stroke categories. The proposed model demonstrated that CNNs can automatically learn discriminative imaging features for stroke detection, although the approach was limited to identifying the presence of stroke without further analysis of disease progression. To improve

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lesion localization, Dobshik et al. [3] developed a modified 3D U-Net architecture incorporating residual connections and squeeze-and-excitation blocks for acute ischemic stroke lesion segmentation in non-contrast CT images. Their segmentation-based approach accurately identified lesion regions but required detailed pixel-level annotations, increasing dataset preparation complexity. Similarly, Fontanella et al. [4] proposed a deep learning framework for detecting acute ischemic stroke lesions using labelled but not fully annotated CT images, reducing the dependency on exhaustive manual annotations while focusing primarily on lesion identification rather than disease staging.

2. Literature Review

Deep learning-based stroke analysis has become an important research direction in medical image interpretation, particularly for CT and MRI-based stroke detection, lesion identification, and automated decision support systems. Ostmeier et al. investigated a CNN-based model for segmenting acute ischemic stroke lesions from non-contrast CT images, demonstrating performance comparable to expert neuroradiologists. Liang et al. proposed a symmetry-enhanced attention network that utilizes anatomical symmetry between brain hemispheres to improve lesion segmentation. Although both methods achieved accurate lesion localization, they mainly focused on pixel-level segmentation rather than providing stroke classification, stage prediction, and severity estimation within a single framework [5], [6]. Gheibi et al. introduced the CNN-Res model for ischemic stroke lesion segmentation using MRI images, while Ryu et al. developed a deep learning approach for ischemic stroke subtype classification using diffusion-weighted MRI and atrial fibrillation information. These methods addressed lesion segmentation and subtype prediction but did not perform stage-wise stroke classification or severity assessment as proposed in the current work [7], [8]. Qasrawi et al. proposed a hybrid ensemble deep learning model for ischemic stroke detection and classification, whereas Xue et al. employed an EfficientNet-based CNN for stroke detection from MRI images. Although both studies achieved reliable detection performance, they primarily focused on identifying stroke without incorporating stage classification or severity estimation [9], [10]. Qari presented a transformer-based transfer learning model for brain stroke classification using CT images, while Abdi et al. proposed a CNN-based framework for binary stroke detection. Although these approaches demonstrated effective image classification, they were limited to stroke identification and did not extend to hierarchical stage prediction or severity analysis [11], [12]. Mridha et al. developed an explainable machine learning model for stroke prediction using clinical data, and Yu et al. proposed a multimodal deep learning framework based on ECG and PPG signals for stroke risk prediction. Both approaches relied on non-imaging data, whereas the proposed system performs stroke analysis directly from CT/MRI brain images using CNN models [13], [14]. Mak et al. introduced an EEG-guided augmented reality system for detecting stroke-induced spatial neglect, while Lv et al. proposed a multimodal deep learning network for ischemic stroke prediction using multiple MRI sequences. These studies focused on neurological assessment and risk prediction rather than hierarchical image-based stroke stage classification [15], [16]. Mainali et al. reviewed recent machine learning and deep learning techniques for stroke diagnosis, lesion segmentation, and outcome prediction. Lee et al. developed a machine learning model to estimate the thrombolysis treatment window using DWI and FLAIR MRI images. While these studies demonstrated the potential of AI in stroke management, they did not provide an integrated framework for stroke detection, stage classification, and severity estimation [17], [18]. Babutain et al. proposed a deep learning framework for automated ischemic stroke detection using CT images, whereas Rehman introduced a hybrid deep learning model for stroke risk prediction using clinical data. Although both methods showed promising prediction performance, they focused on detection or risk assessment rather than a comprehensive multi-level classification system. The proposed framework addresses this limitation by integrating binary detection, stage classification, and feature-based severity estimation within a unified deep learning pipeline [19], [20].

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3. Methodology

The implementation methodology of the proposed stroke disease prediction system follows a hierarchical deep learning framework, as illustrated in Figure 1. The framework processes brain scan images through sequential stages, including dataset preparation, image preprocessing, CNN-based binary stroke detection, stage-wise stroke classification, and feature-based severity estimation using the K-Means clustering algorithm. Initially, the system determines whether the uploaded brain scan is Normal or Stroke. If a stroke is detected, a second CNN model classifies the image into Stage 1, Stage 2, or Stage 3 based on the learned deep features. The extracted feature maps are then analyzed to estimate the severity level as Low, Medium, or High by combining clustering results with the model confidence score and stage-based risk information. Finally, the system generates an interpretable prediction report containing the detected class, stroke stage, confidence score, severity level, and care recommendations. The complete framework is deployed as a Flask-based web application, enabling users to upload brain scan images and obtain accurate real-time predictions through an interactive and user-friendly interface.

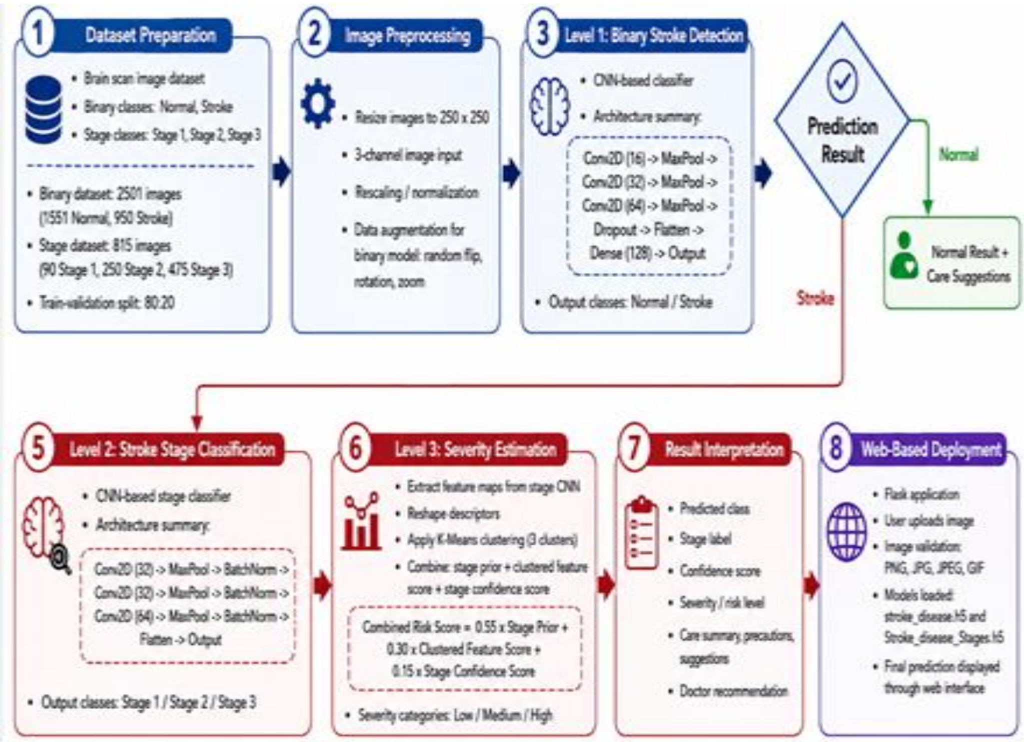

Figure 1 Workflow of the proposed CNN-based brain stroke detection and severity assessment system

3.1. Dataset Description

The dataset comprises brain scan images organized for a hierarchical stroke prediction system with two components: binary stroke detection and stage classification. For the first prediction level, the binary dataset contains two classes—Normal and Stroke—used to train the primary CNN model for determining whether a brain scan contains stroke-related features. A total of 2501 images are utilized, consisting of 1551 Normal images and 950 Stroke images, with an 80:20 train-validation split. Each input image is resized to 250×250 pixels as a three-channel input (250×250×3) before being passed to the CNN model. Pixel values are normalized from the 0-255 range to 0-1 using a rescaling layer, and data augmentation techniques including random horizontal flipping, random rotation, and random zoom are applied to improve model generalization. For the second prediction level, a separate stage classification dataset contains only stroke-related images divided into three classes: Stage 1, Stage 2, and Stage 3. A total of 815 images are used, with 90 images in Stage

1, 250 images in Stage 2, and 475 images in Stage 3. This dataset trains the second CNN model for stage-wise classification after stroke detection. All images maintain consistent 250×250 pixel dimensions with three channels, and identical preprocessing steps including normalization and augmentation are applied.The dataset exhibits class imbalance, particularly in the stage classification dataset where Stage 1 has significantly fewer samples compared to Stage 2 and Stage 3. This imbalance represents a limitation, potentially affecting the model's ability to learn equally from all stroke stages and influencing classification performance. The unequal distribution must be considered when interpreting results, and future work may address this through techniques such as oversampling, undersampling, or synthetic data generation. Despite this limitation, the dataset effectively supports a multi-level prediction structure enabling sequential stroke detection, stage classification, and severity estimation within a comprehensive hierarchical framework.

3.2.Dataset Preprocessing

The project uses brain scan image datasets arranged according to the prediction task. For the first level of classification, the dataset is divided into two classes: Normal and Stroke. This dataset is used to train the primary Convolutional Neural Network model for binary stroke detection. The binary dataset contains 2501 images, including 1551 Normal images and 950 Stroke images. The dataset is split into training and validation subsets using an 80:20 split. For the second level of classification, a separate stroke stage dataset is used. This dataset contains only stroke-related brain scan images and is divided into three classes: Stage 1, Stage 2, and Stage 3. The stage classification dataset contains 815 images, including 90 Stage 1 images, 250 Stage 2 images, and 475 Stage 3 images. This dataset is used to train the second CNN model for stage-wise stroke classification.

3.3.Image Preprocessing

Before training and prediction, all brain scan images are converted into a fixed input size of 250 × 250 pixels. This resizing step ensures that all images have a uniform shape and can be passed consistently into the deep learning models. The images are treated as three-channel inputs with a shape of 250× 250 × 3. For the binary CNN model, pixel normalization is performed using a rescaling layer. The original pixel values, which normally range from 0 to 255, are converted into values between 0 and 1. This improves the stability of model training and helps the neural network learn image features more effectively. Data augmentation techniques are also applied in the binary classification model, including random horizontal flipping, random rotation, and random zoom. These augmentation operations help the model learn variations in image appearance and reduce overfitting.

3.4.Binary Stroke Detection Model

The first prediction stage uses a Convolutional Neural Network to classify the input brain scan image as either Normal or Stroke. This model acts as the primary screening layer of the system. The binary CNN architecture begins with data augmentation and image rescaling, followed by multiple convolution and pooling layers. The model contains three convolutional blocks. The first convolutional layer uses 16 filters, the second convolutional layer uses 32 filters, and the third convolutional layer uses 64 filters. Each convolutional layer applies the ReLU activation function to learn non-linear image features. MaxPooling layers are used after the convolutional layers to reduce the spatial dimensions of the feature maps while retaining important visual information. A dropout layer is included to reduce overfitting. The extracted features are then flattened and passed to a dense layer with 128 neurons. The final output layer contains two output units corresponding to the two classes: Normal and Stroke. During prediction, the model produces class scores, which are converted into probabilities using the softmax function. The class with the highest probability is selected as the final binary prediction. If the model predicts the image as Normal, the system directly displays the Normal result along with the confidence score and care suggestions. If the model predicts Stroke, the image is forwarded to the second-level stage classification model.

3.5.Stroke Stage Classification Model

The second prediction stage is activated only when the first CNN model detects stroke-related features. This stage uses another CNN model to classify the stroke image into Stage 1, Stage 2, or Stage 3. The stage classification model is designed with convolutional layers, max pooling layers, batch normalization layers, a flattening layer, and a dense output layer. The first convolutional layer uses 32 filters, followed by max pooling and batch normalization. The second convolutional layer also uses 32 filters, followed by another max pooling and batch normalization layer. The third convolutional layer uses 64 filters, followed by max pooling and batch normalization. Batch normalization is used to stabilize learning and improve training performance by normalizing intermediate feature representations. After feature extraction, the output is flattened and passed to a dense layer with three output units corresponding to Stage 1, Stage 2, and Stage 3. The stage model predicts the probability of each stage, and the stage with the highest probability is selected as the final stage output. This stage-wise prediction allows the system to provide more detailed interpretation after stroke detection rather than stopping at a binary result.

3.6.CNN Feature Extraction for Severity Estimation

After the stage is predicted, the system performs severity estimation using feature maps extracted from the trained stage classification CNN model. Instead of relying only on the final. stage prediction, the system uses intermediate CNN feature representations to estimate the risk level. In the implementation, a feature extractor model is created from the trained stage CNN by selecting the output of the intermediate feature map layer. This extracted feature map contains learned spatial patterns from the brain scan image. The feature map is reshaped into a set of feature descriptors. These descriptors represent the internal deep features learned by the CNN from the stroke image. The feature descriptors are then passed to the severity estimation module for clustering-based analysis.

3.6.1.G.K-Means-Based Severity Estimation

The severity estimation module utilizes the feature maps extracted from the stage classification CNN model to estimate the severity level of the detected stroke. The extracted feature descriptors are clustered into three groups using the K-Means clustering algorithm implemented in OpenCV. These clusters represent low-, medium-, and high-strength feature representations learned by the CNN. The strength of each cluster is determined by computing the norm of its corresponding cluster center. Based on the cluster strengths, a clustered feature score is calculated from the distribution of feature descriptors. To obtain a comprehensive severity estimate, the clustered feature score is combined with the predicted stage and the CNN confidence score. The final severity score is computed using three components: Stage prior score based on the predicted stroke stage. Clustered feature score obtained from K-Means clustering. Stage confidence score derived from the CNN prediction probability. The predefined stage prior scores are assigned as Stage 1 = 0.25, Stage 2 = 0.55, and Stage 3 = 0.85. The final combined risk score is calculated using weighted fusion as Based on the combined risk score, the severity level is categorized as:

- **Low Risk:** Score < 0.40
- **Medium Risk:** 0.40 ≤ Score < 0.70
- **High Risk:** Score ≥ 0.70

This severity estimation approach provides an additional interpretive layer beyond stage classification, enabling the proposed system to deliver a more comprehensive assessment of stroke severity for clinical decision support.

4. Results and Discussions

The proposed stroke disease prediction systemwas evaluated at two major levels: binary stroke detection and stroke stage classification. The first model was evaluated for its ability to classify brain scan images into Normal and Stroke classes, while the second model was evaluated for classifying stroke-positive images into Stage 1, Stage 2, and Stage 3. In addition to these classification outputs, the system also generated a severity score using CNN-extracted feature maps and K-Means Clustering.

4.1.Evaluation of Binary Stroke Detection Model

The binary stroke detection model was trained using a brain scan image dataset containing two classes: Normal and Stroke. The dataset consisted of 2501 images, including 1551 Normal images and 950 Stroke images. The dataset was divided into training and validation sets using an 80:20 split. Each image was resized to 250 × 250 pixels and normalized before being passed into the CNN model. The binary CNN model achieved a final training accuracy of

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98.85% and a validation accuracy of 97.00%. The final validation loss was 0.2078. These results indicate that the model was able to learn discriminative visual patterns for identifying stroke-related image features from brain scan images. The validation accuracy shows that the model performed effectively on unseen validation data during training. The classification report generated for the binary classification task showed strong class-wise performance. For the Normal class, the model achieved a precision of 0.99, recall of 0.99, and F1-score of 0.99. For the Stroke class, the model achieved a precision of 0.98, recall of 0.98, and F1-score of 0.98. The overall dataset-level classification accuracy was approximately 0.99. This dataset-level evaluation should be interpreted carefully because it was generated on the available image directory and should not be treated as a separate independent test-set result unless an unseen test dataset is used Shown in Table 1.

Table 1 Performance Metric of the Model

Metric	Value
Training Accuracy	98.85%
Validation Accuracy	97.00%
Validation Loss	0.2078
Overall Accuracy	99.00%

4.2.Evaluation of Stroke Stage Classification Model

The stage classification model was evaluated using a separate stroke stage dataset containing three classes: Stage 1, Stage 2, and Stage 3. The dataset contained 815 stroke images, including 90 Stage 1 images, 250 Stage2 images, and 475 Stage 3 images. Similar to the binary model, the images were resized to 250 × 250 pixels before training. The stage classification CNN achieved a maximum validation accuracy of 95.71% during training. The final validation accuracy was 93.25%. These results show that the model was able to classify stroke images into stage-wise categories with strong validation performance. The use of convolutional layers, max-pooling layers, and batch normalization helped the model learn stage-specific visual features from the brain scan images. The performance metrics of the Proposed Binary Stroke Detection model is shown below. The classification report for the stage classification model showed high performance across all three stroke stages. For Stage 1, the model achieved a precision of 1.00, recall of 0.86, and F1-score of 0.92. For Stage 2, the model achieved a precision of 0.95, recall of 1.00, and F1-score of 0.97. For Stage 3, the model achieved a precision of 0.99, recall of 0.99, and F1-score of 0.99. The overall dataset-level classification accuracy was approximately 0.98. The comparatively lower recall for Stage 1 may be due to the smaller number of Stage 1 images in the dataset when compared with Stage 2 and Stage 3.

4.3.Severity Estimation Evaluation

The proposed system also estimates the severity level after stroke stage classification. Severity estimation is performed by extracting feature maps from the stage classification CNN and applying K-Means clustering to the extracted features. The feature descriptors are grouped into three clusters, and the cluster distribution is used to calculate a clustered feature score. The final severity score is computed by combining thepredicted stage prior, clustered feature score, and stage confidence score. The weighted risk score is calculated as: Combined Risk Score = 0.55 × Stage Prior Score + 0.30 × Clustered Feature Score + 0.15 × Stage Confidence ScoreBased on the combined risk score, the system classifies severity into Low, Medium, or High. The stage prior scores used in the implementation are 0.25 for Stage 1, 0.55 for Stage 2, and 0.85 for Stage 3. The risk bands are defined as Low for scores below 0.40, Medium for scores below 0.70, and High for scores of 0.70 and above. This severity estimation moduleprovides an additional interpretive output beyond direct CNN classification.

Conclusion

This project presents a hierarchical deep learning-based framework for stroke disease prediction from brain scan images. The system successfully implements a multi-level approach that performs binary stroke detection, stage-wise classification, and severity estimation within a single integrated pipeline. By utilizing separate CNN models for detection and stage classification, combined with K-Means clustering for severity assessment, the system provides comprehensive and interpretable outputs that extend beyond simple binary classification. The implementation demonstrates the feasibility of developing a screening-oriented decision-support system using deep learning technique. The Flask-based web application enables users to upload brain scan images and receive detailed predictions including class labels, confidence scores, severity levels, and care-related suggestions. The system effectively integrates multiple prediction levels, making it more informative than conventional single-task models. Despite the promising results, certain limitations must be acknowledged. The class imbalance in the stage classification dataset, particularly the underrepresentation of Stage 1 images, represents a constraint that may affect model generalization. Additionally, the system is designed as a screening tool and should not replace professional medical diagnosis, as all predictions require clinical verification by healthcare specialists. The proposed system contributes to the development of AI-assisted stroke screening tools, offering a practical and scalable solution for preliminary stroke assessment from brain scan images.

Future Enhancement

Future work should focus on addressing dataset limitations by collecting larger and more balanced stroke stage images. Severity estimation could be improved using clinically validated labels and additional imaging modalities. Implementation of explainable AI techniques would enhance model interpretability and clinical trust. Integration of patient clinical data with imaging features could provide more comprehensive risk assessment. Deployment could be expanded beyond web-based applications to mobile platforms and hospital systems. Cross-validation on external datasets would assess model generalizability across different clinical settings. Emerging deep learning architectures and ensemble methods could further improve prediction performance, while federated learning would enable collaborative training across institutions while preserving patient privacy.

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References

[1]. Cui, L., Liu, Y., Wang, X., & Wang, H. (2022). Deep learning in ischemic stroke imaging analysis. Frontiers in Neurology.
[2]. Ozaltin, O., Coskun, O., Yeniay, O., & Subasi, A. (2022). A deep learning approach for detecting stroke from brain CT images using OzNet. Bioengineering, 9(12), 783.
[3]. Dobshik, A. V., Verbitskiy, S. K., Pestunov, I. A., Sherman, K. M., Sinyavskiy, Y. N., Tulupov, A. A., & Berikov, V. B. (2023). Acute ischemic stroke lesion segmentation in non-contrast CT images using 3D convolutional neural networks. Computer Optics.
[4]. Fontanella, A., Li, W., Mair, G., Antoniou, A., Platt, E., Armitage, P., Trucco, E., Wardlaw, J., & Storkey, A. (2024). Development of a deep learning method to identify acute ischaemic stroke lesions on brain CT. Stroke and Vascular Neurology.
[5]. Ostmeier, S., Axelrod, B., Verhaaren, B. F. J., Christensen, S., Mahammedi, A., Liu, Y., Pulli, B., Li, L. J., Zaharchuk, G., & Heit, J. J. (2023). Non-inferiority of deep learning ischemic stroke segmentation on non-contrast CT compared to expert neuroradiologists. Scientific Reports, 13, 16285.
[6]. Liang, K., Han, K., Li, X., Cheng, X., Li, Y., Wang, Y., & Yu, Y. (2021). Symmetry-enhanced attention network for acute ischemic infarct segmentation with non-contrast CT images. arXiv preprint.
[7]. Gheibi, Y., et al. (2023). CNN-Res: Deep learning framework for segmentation of acute ischemic stroke lesions. BMC Medical Informatics and Decision Making.
[8]. Ryu, W. S., et al. (2024). Deep learning-based automatic classification of ischemic stroke subtype using diffusion-
[9]. weighted imaging and atrial fibrillation data. [Journal details to be added based on final source].
[10]. Qasrawi, R., et al. (2024). Hybrid ensemble deep learning model for advancing ischemic brain stroke detection and classification. [Journal details to be added based on final

source].
[11]. Xue, X., et al. (2025). An efficient deep learning network for brain stroke detection using brain MRI. [Journal details to be added based on final source.
[12]. Qari, S. (2025). Brain stroke classification using CT scans with transformer-based transfer learning. [Journal details to be added based on final source].
[13]. Abdi, H., et al. (2025). Stroke detection in brain CT images using convolutional neural networks. Information, 16(5), 345.
[14]. Mridha, K., Ghimire, S., Shin, J., Aran, A., Uddin, M. M., & Mridha, M. F. (2023). Automated stroke prediction using machine learning: An explainable and exploratory study with a web application for early intervention. IEEE Access, 11, 52288–52312
[15]. Yu, J., Park, S., Kwon, S. H., Cho, K. H., & Lee, H. (2022).AI-based stroke disease prediction system using ECG and PPG bio-signals. IEEE Access.
[16]. Mak, J., Kocanaogullari, D., Huang, X., Kersey, J., Shih, M., Grattan, E. S., Skidmore, E. R., Wittenberg, G. F., Ostadabbas, S., & Akcakaya, M. (2022). Detection of stroke-induced visual neglect and target response prediction using augmented reality and electroencephalography. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 30, 1840–1850.
[17]. Lv, P., Yang, J., Wang, J., Guo, Y., Tang, Q., Magnier, B., Lin, J., & Zhou, J. (2023). Ischemic stroke prediction of patients with carotid atherosclerotic stenosis via multi-modality fused network. Frontiers in Neuroscience, 17, 1118376.
[18]. Mainali, S., Darsie, M. E., & Smetana, K. S. (2021). Machine learning in action: Stroke diagnosis and outcome prediction. Frontiers in Neurology, 12, 734345.
[19]. Lee, H., Lee, E. J., Ham, S., Lee, H. B., Lee, J. S., Kwon, S. U., Kim, J. S., Kim, N., & Kang, D. W. (2020). Machine learning approach to identify stroke within 4.5 hours. Stroke.
[20]. Babutain, K., Hussain, M., Aboalsamh, H., & Al-Hameed, M. (2021). Deep learning-enabled detection of acute ischemic stroke using brain computed tomography images. International Journal of Advanced Computer Science and Applications, 12(12).