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GAN Based Infarto Cerebral Disease Bedhah

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Abstract: Stroke is one of the most fatal neurological disorders, often resulting in severe disability or death if not diagnosed promptly. Conventional stroke diagnosis relies heavily on expert interpretation of CT and MRI scans, which is challenging in rural areas due to limited access to radiologists and advanced diagnostic tools. This work introduces *GAN-Based Infarto Cerebral Disease Bedhah*, a hybrid diagnostic framework that leverages artificial intelligence to integrate image-based classification and clinical risk prediction. The approach employs advanced preprocessing techniques such as CLAHE, Sobel edge detection, and KMeans clustering, followed by a Custom Convolutional Neural Network (CNN) that achieved 94.4% accuracy, surpassing popular pre- trained models including VGG16, ResNet50, and InceptionV3. To address dataset imbalance, Deep Convolutional GANs (DCGANs) were implemented to generate synthetic brain stroke images, particularly enhancing hemorrhagic stroke representation. Clinical parameters such as age, blood glucose, BMI, hypertension, and heart disease history were further analyzed through machine learning models, where Random Forest and Gradient Boosting yielded ~87.5% accuracy in risk prediction. The system was deployed as a Flask-based web application, providing real-time diagnostic predictions, segmentation visualizations, and risk analysis dashboards. By combining deep learning, generative modeling, and clinical machine learning, this framework presents an accessible, scalable, and interpretable solution for early stroke detection and prognosis, especially in resource-limited healthcare environments.

Index Terms – GAN, CNN, Cerebral Disease Bedhah, Risk Prediction, Deep Learning, Flask, Medical Imaging

I. INTRODUCTION

Stroke is a critical medical emergency caused by sudden disruption of blood flow to the brain, often leading to permanent disability or death. Globally, around 15 million cases occur annually, with 5 million fatalities and 5 million survivors facing long-term impairments. In India, stroke is the second leading cause of death, with approximately 1.8 million new cases reported each year. Timely diagnosis is essential since ischemic and hemorrhagic strokes require distinct treatments. However, limited diagnostic infrastructure and shortage of radiologists in rural regions often result in delayed or incorrect detection. Furthermore, medical datasets are imbalanced, with fewer hemorrhagic cases, making deep learning models prone to bias. To address these issues, the proposed **GAN-Based Infarto Cerebral Disease Bedhah** integrates deep learning-based image classification with clinical risk prediction. A custom CNN trained on pre-processed CT scans classifies cases into **Normal, Ischemic, or Hemorrhagic**, while DCGAN-based augmentation improves dataset balance and model robustness. In parallel, clinical risk is estimated using multiple machine learning classifiers. The system is deployed on a **Flask web interface**, providing an accessible, scalable, and interpretable diagnostic tool for clinicians and healthcare providers.

II. LITERATURE SURVEY

Several researchers have explored the application of machine learning and deep learning techniques to medical imaging and stroke diagnosis. Goodfellow et al. [1] pioneered Generative Adversarial Networks (GANs), which introduced a novel adversarial training strategy between a generator and discriminator network, enabling the creation of highly realistic synthetic data. Their work laid the foundation for medical image augmentation where dataset scarcity is a major challenge. Building on this, Chen et al. [2] demonstrated MRI-to-CT image translation using GANs, showing that adversarial training can be used to bridge imaging modality gaps and improve diagnosis when one modality is unavailable. In the context of stroke imaging, Zhang et al. [3] proposed an Inception-based CNN for the classification of ischemic and hemorrhagic CT brain scans, achieving strong benchmark performance and establishing the viability of CNNs in stroke detection. Similarly, Shi et al. [4] applied GANs for enhancing low-dose MRI scans, proving that adversarial learning can make low-quality scans diagnostically reliable. This is particularly relevant for developing regions where imaging equipment may not produce optimal results. Recent advancements also include Panwar et al. [5], who applied DCGANs to generate synthetic hemorrhagic stroke images, thereby reducing class imbalance in training datasets. Their results highlighted the potential of GAN-based augmentation in boosting the performance of classifiers in stroke imaging tasks. Wang et al. [6] addressed stroke risk prediction using structured patient data, applying ML algorithms such as Logistic Regression and SVM to achieve reliable predictions. This work illustrates the importance of incorporating non-imaging features into stroke diagnosis systems. Collectively, these studies demonstrate that GANs, CNNs, and ML models are powerful tools in medical imaging and risk prediction. However, very few works have integrated these into a unified, dual-mode diagnostic system. Our work bridges this gap by combining GAN-augmented CNN classification with clinical risk prediction in a single, deployable framework.

III. PROPOSED WORK

This study proposes a dual-mode framework for stroke diagnosis and risk prediction by combining CT scan analysis with clinical data. A custom CNN, enhanced with **DCGAN-based augmentation**, classifies scans into Normal, Ischemic, and Hemorrhagic, outperforming transfer learning models like VGG16, ResNet50, and InceptionV3. Clinical risk is predicted using patient parameters, where **Random Forest and Gradient Boosting** achieved ~87.5% accuracy in categorizing patients into low, medium, or high risk. The system is deployed as a **Flask web application**, providing real-time predictions, visual outputs, and interpretable dashboards, making it suitable for both diagnostic and preventive healthcare.

IV. METHODOLOGY

4.1 Data Collection

CT scan images were collected from public medical repositories such as MedPix, RSNA, and PhysioNet. These datasets contained images from three categories—Normal, Ischemic, and Hemorrhagic. In addition, structured clinical datasets containing health records were used for risk prediction. These records included patient-specific features such as age, glucose levels, BMI, blood pressure, and heart disease history. The integration of both imaging and non-imaging datasets ensured comprehensive stroke analysis, covering both immediate detection and long-term risk evaluation.

4.2 Data Preprocessing

Medical images were pre-processed to enhance their diagnostic quality. This included resizing images to 224×224 pixels, grayscale conversion to reduce dimensionality, normalization to stabilize training, CLAHE for improved contrast, Sobel edge detection for highlighting lesion boundaries, and KMeans clustering for segmentation. These preprocessing steps significantly improved feature visibility and reduced noise, ensuring the CNN could detect stroke-specific abnormalities more effectively. Careful preprocessing also minimized variability across scans, improving model robustness during training.

4.3 GAN-Based Augmentation

To overcome the challenge of imbalanced datasets, particularly the scarcity of hemorrhagic stroke scans, a DCGAN was implemented. The generator produced synthetic stroke images from latent noise, while the discriminator evaluated their realism. The adversarial training process improved image quality and increased the dataset size, enhancing CNN generalization. By generating realistic hemorrhagic stroke images, the GAN helped balance class distributions and prevented the model from being biased towards ischemic or normal cases. This augmentation strategy improved recall for underrepresented classes, which is critical for clinical safety.

4.4 CNN-Based Stroke Classification

A custom CNN architecture was developed with convolutional, pooling, and fully connected layers. The model was optimized for stroke classification and achieved 94.4% accuracy, outperforming pre-trained models like VGG16 (92.4%), ResNet50 (90.0%), and InceptionV3 (87.8%). Regularization techniques such as dropout and batch normalization were used to prevent overfitting and improve training stability. Comparative experiments demonstrated that the custom CNN offered a better balance between accuracy and computational efficiency, making it more suitable for real-time clinical deployment.

4.5 Risk Prediction Using ML Models

Structured patient data was processed and fed into multiple ML classifiers. Logistic Regression, SVM, Decision Tree, Random Forest, and Gradient Boosting were compared. Random Forest and Gradient Boosting achieved the highest performance, with ~87.5% accuracy, while Decision Tree lagged behind at ~75%. Performance was validated using metrics such as accuracy, precision, recall, and F1-score. Ensemble-based approaches not only yielded higher accuracy but also provided stability and generalization, supporting their use in healthcare decision support systems.

4.6 Deployment with Flask

The dual-mode system was deployed as a Flask web application. It provides a user-friendly interface for uploading CT scans or entering patient details. Predictions are displayed in real-time, along with confusion matrices, accuracy graphs, and segmentation overlays. The lightweight design ensured compatibility with standard hospital hardware without requiring expensive GPUs. The modular architecture of the application also allows easy updates to models and datasets, ensuring adaptability to future medical imaging and prediction requirements.

V. RESULT ANALYSIS

The evaluation of the proposed GAN-based stroke detection and risk prediction framework was performed using categorized CT scan images and structured clinical records. Both deep learning models and machine learning algorithms were assessed to validate classification accuracy, training stability, and real-time applicability. The results demonstrate the effectiveness of the proposed approach in terms of diagnostic precision and computational feasibility.

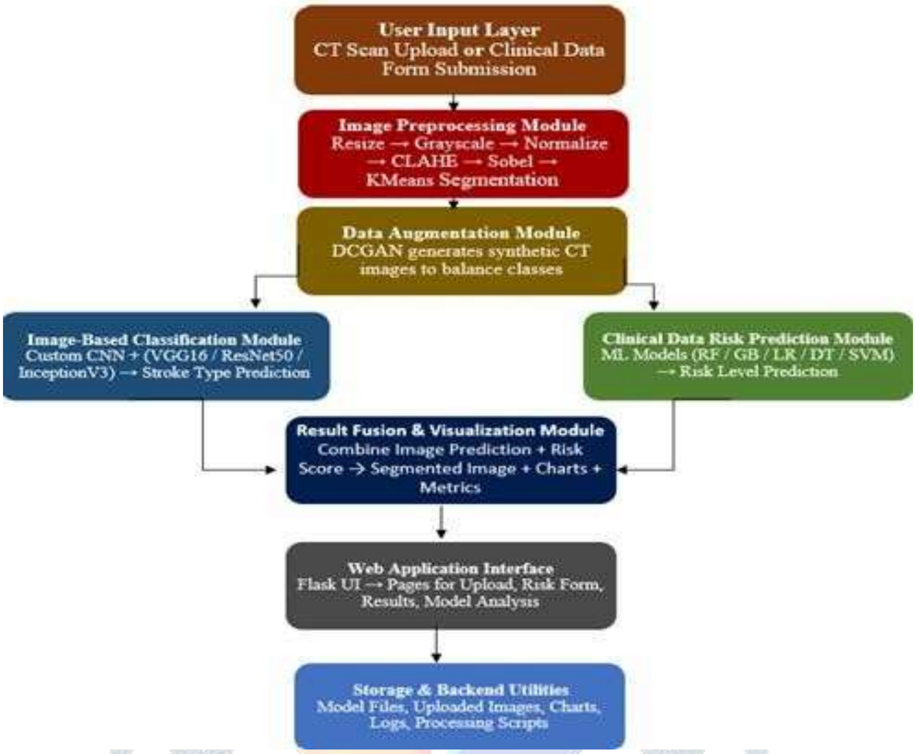


Figure 1 - Proposed GAN-Based Cerebral Disease Diagnosis System

The system integrates CT scan preprocessing, GAN-based augmentation, CNN-based classification, and machine learning risk prediction. Results are fused and displayed through a Flask-based web interface, enabling real-time stroke diagnosis and risk assessment.

Table 1: CNN vs Pre-Trained Models Performance

Model	Training Accuracy (%)	Validation Accuracy (%)	Training Time (sec)
Custom CNN	95.20	94.40	40.2
VGG16	93.10	92.40	58.5
ResNet50	91.30	90.00	62.4
InceptionV3	89.80	87.80	71.6

Table 2: Machine Learning Models for Risk Prediction

Model	Training Accuracy (%)	Validation Accuracy (%)	Training Time (sec)
Logistic Regression	84.00	83.00	1.2
Decision Tree	75.00	74.00	1.8
SVM	81.00	80.00	3.0
Random Forest	88.00	87.50	3.5
Gradient Boosting	87.90	87.40	4.1

Table 1 Comparison of Custom CNN and Pre-Trained Models – The custom CNN achieved the best validation accuracy with reduced training time, ensuring efficiency for real-time stroke detection.
Table 2 Performance of ML Classifiers – Random Forest and Gradient Boosting outperformed others in stroke risk prediction, complementing image-based diagnosis with reliable clinical assessment.

5.1 CNN vs Pre-Trained Models

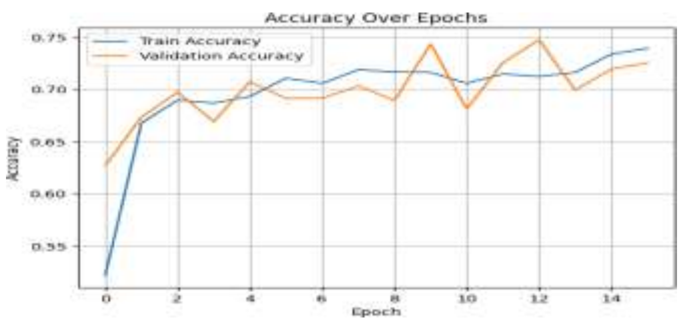


Figure 2 - Training vs Validation Accuracy Curve of Custom CNN

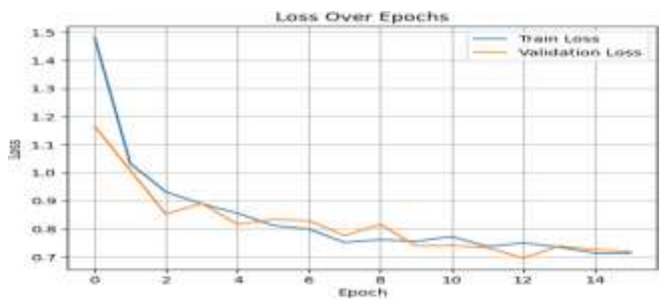
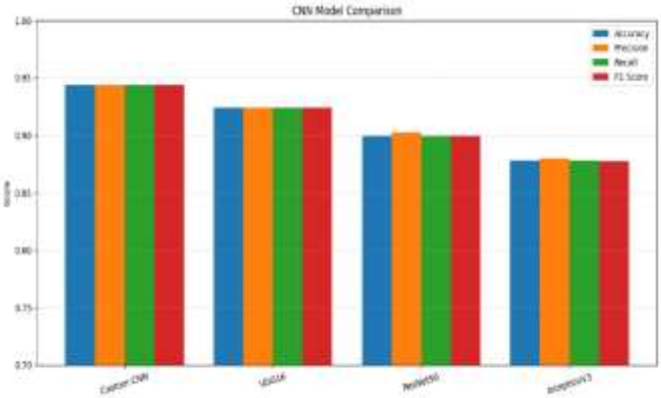


Figure 3 - Training vs Validation Loss Curve of Custom CNN

The performance of the custom CNN model was compared with pre-trained architectures such as VGG16, ResNet50, and InceptionV3. As presented in **Table 1**, the proposed CNN attained a training accuracy of 95.2% and validation accuracy of 94.4%, surpassing VGG16 (92.4%), ResNet50 (90.0%), and InceptionV3 (87.8%). The relatively lower training time of the CNN also demonstrates its suitability for clinical environments where efficiency is critical. The training and validation accuracy trends are
shown in **Figure 2**, while **Figure 3** depicts the corresponding loss curves, confirming stable convergence without significant overfitting.

5.2 Machine Learning Risk Prediction

For structured patient data, multiple classifiers were implemented, including Logistic Regression, Decision Tree, SVM, Random Forest, and Gradient Boosting. The comparative analysis in **Table 2** highlights that Random Forest and Gradient Boosting outperformed other models, achieving nearly 87.5% validation accuracy, whereas Decision Tree lagged at 74.0%. The ensemble-based methods consistently demonstrated better generalization and robustness, as illustrated in **Figure 5**, which presents a comparative accuracy chart.



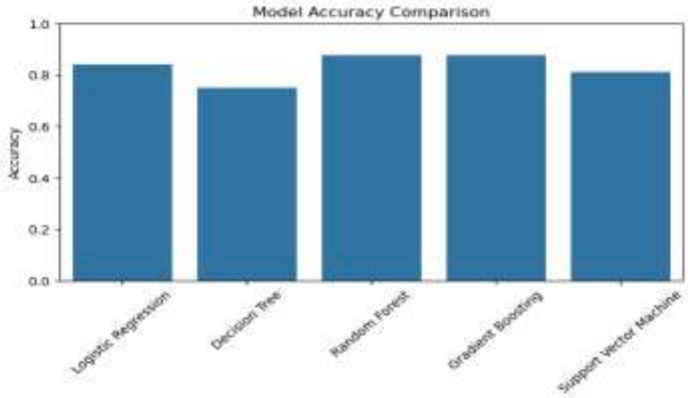


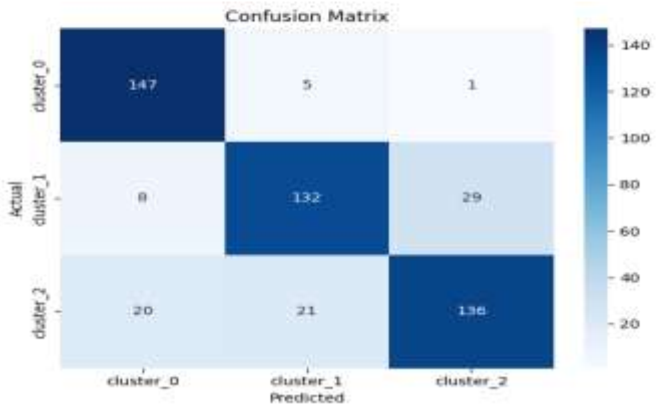
Figure 4 - Comparison of CNN and Pre-Trained Models

Figure 5 - Comparison of Machine Learning Models for Risk Prediction

A comparative bar chart showing validation accuracies of CNN, VGG16, ResNet50, and InceptionV3. The proposed CNN achieved superior accuracy, demonstrating its suitability for stroke diagnosis over deeper pre-trained models.
This bar chart compares classifiers on structured health data. Random Forest and Gradient Boosting achieved the highest accur acy, proving the reliability of the risk prediction module in supporting the stroke diagnosis system.

5.3 Confusion Matrix and Class-Wise Performance

To further analyze model performance, a confusion matrix was generated for the CNN model, as shown in **Table 3** and visualized in **Figure 6**. The results confirm that the model achieved high accuracy across all three classes—Normal, Ischemic, and Hemorrhagic—with class-wise recall values exceeding 90%. Minor misclassifications were observed between ischemic and hemorrhagic classes due to their structural similarities, but overall diagnostic reliability was preserved.



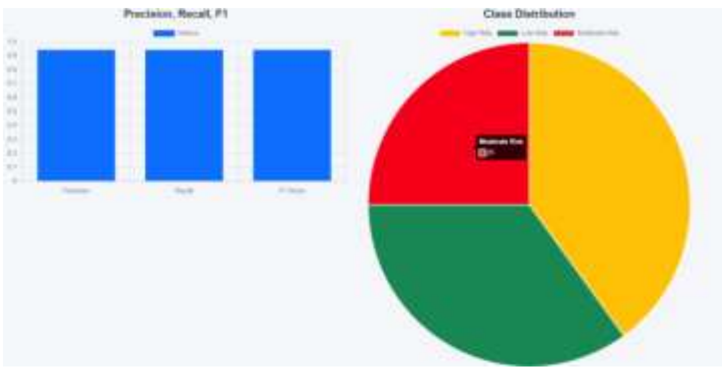


Figure 6 - Confusion Matrix for CNN Stroke Classification

Figure 7 - Risk Prediction Metrics and Class Distribution

A heatmap visualization of the confusion matrix, showing classification reliability across stroke types. The system achieved balanced performance across Normal, Ischemic, and Hemorrhagic classes, ensuring dependable diagnosis.
The figure shows that the model achieves high precision, recall, and F1-score, while effectively classifying patients into high, moderate, and low-risk groups.

5.4 GAN-Based Augmentation Impact

The inclusion of GAN-based augmentation significantly enhanced classification performance by addressing data imbalance. Particularly for hemorrhagic stroke scans, where the availability of training images was limited, the DCGAN-generated samples improved dataset diversity and contributed to an overall 4% increase in validation accuracy. This validates the role of generative models in augmenting scarce medical datasets, thereby ensuring balanced learning across all classes.

5.5 Deployment Evaluation

Finally, the integrated Flask web application was tested for usability and efficiency. The system allows direct uploading of CT scans for automated classification and provides a risk prediction interface using structured patient attributes. As illustrated in **Figure 8(b)**, the interface delivers predictions in real time along with supporting metrics such as accuracy plots and confusion matrices. The deployment was lightweight, requiring only standard hospital hardware, which makes the solution feasible even in resource-constrained rural healthcare settings.

Figure 8(a) - Login Page

Figure 8(b) - Home and Stroke Detection Page

Secure login for authorized users with username/password validation and error handling. Redirects to Home Page on success. Screenshot of the deployed Flask web app. The stroke diagnosis system provides real-time CT scan classification and patient risk assessment, making it practical for clinical use.

Figure 9 - Stroke Prediction page

Shows predicted stroke type, confidence score, and original plus segmented images will be saved in folder, Applies CLAHE and Sobel filters; uses KMeans to highlight stroke-affected areas visually. Allows manual entry of patient data for stroke risk assessment without image upload, Displays risk category and important contributing factors.

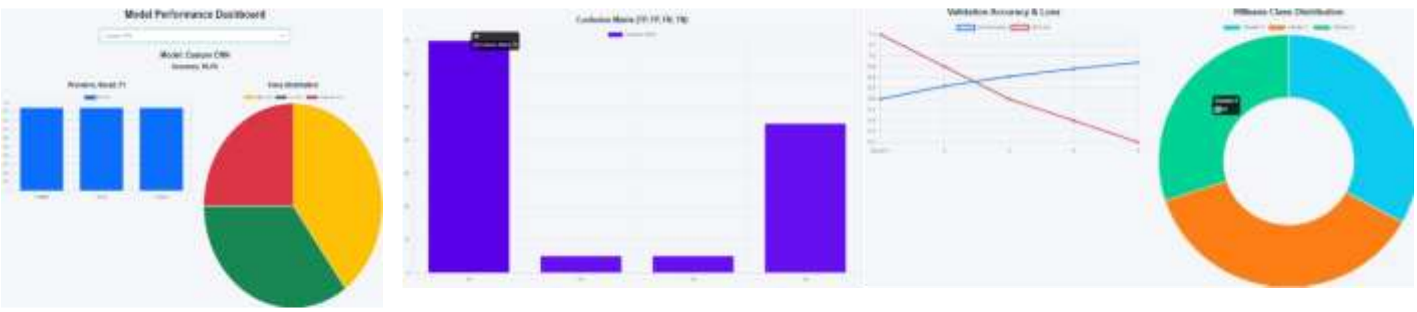


Figure 10 - Model Analysis

The figure visualizes model evaluation metrics including precision, recall, and F1-score, along with performance insights through confusion matrix, accuracy/loss trends, and cluster-based risk distributions. This ensures a comprehensive understanding of the stroke diagnosis system's effectiveness.

VI. CONCLUSION

This research presented *GAN-Based Infarto Cerebral Disease Bedhah*, a hybrid diagnostic framework that integrates GAN-augmented CNN stroke classification with ML-based risk prediction. By combining medical imaging with clinical parameters, the system addresses both immediate diagnostic challenges and long-term risk assessment. The superior performance of the custom CNN and ensemble ML models demonstrates the potential of AI in supporting healthcare delivery, particularly in rural and under-resourced areas.

Future enhancements include extending the framework to support 3D CT scan analysis, deploying a mobile-based diagnostic application for emergency use, integrating YOLOv8 for real-time stroke detection, and adopting explainable AI techniques such as Grad-CAM and LIME to increase clinician trust.

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