Journal of Information Systems Engineering and Management
2025, 10(43s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Neuroimage-Based Stroke Identification: A Machine Learning Approach

Priyanka V. Dhurve [1], Prof. Dr. Nilesh R. Wankhade [2], Mahendra S. Dalvi [3], Santoshchand R. Agrawal [4]
[1] PG Student, Computer Engineering, Late G. N.Sapkal College of Engineering, Nashik, India. Email: priyanka123dhurve@gmail.com
[2] HOD, Department of Computer Engineering, Late G. N.Sapkal College of Engineering, Nashik, India. Email: Nileshrw_2000@gmail.com
[3] Assistant Professor, Department of Computer Engineering, Late G. N.Sapkal College of Engineering, Nashik, India. Email: dalvimahendra21@gmail.com
[4] Assistant Professor, Department of Computer Engineering, Late G. N.Sapkal College of Engineering, Nashik, India. Email: s_ra1976@rediffmail.com

ARTICLE INFO

Received: 24 Dec 2024

Revised: 18 Feb 2025

Accepted: 27 Feb 2025

ABSTRACT

Stroke diagnosis is a time-sensitive process that demands rapid and accurate identification to ensure timely treatment. This study introduces a machine learning-based diagnostic model for stroke detection using neuroimaging data. Stroke remains a major global health concern, contributing to high mortality and disability rates. However, conventional diagnostic techniques, such as CT and MRI scans, often require expert analysis, leading to delays that can reduce treatment effectiveness, especially in acute cases where every minute matters.To address this challenge, our research leverages deep learning to automate stroke detection from neuroimages. We utilized Convolutional Neural Networks (CNN) with InceptionV3 and MobileNet architectures to process brain scans and predict stroke occurrences. InceptionV3, known for its deep convolutional layers that capture intricate image features, and MobileNet, optimized for efficiency and speed, enable both detailed analysis and fast processing. The model was trained on extensive neuroimaging datasets to differentiate between healthy brain tissues and stroke-affected regions. Our results demonstrate high accuracy in stroke identification, highlighting the model's potential to assist healthcare professionals in faster and more precise diagnoses. Integrating this machine learning model into existing diagnostic workflows could significantly reduce the time to diagnosis, allowing for earlier treatment and improved patient outcomes. By combining speed, accuracy, and automation, this approach has the potential to enhance stroke care and alleviate the economic burden associated with delayed treatment.

Keywords: Stroke Identification, Machine Learning, Neuroimages, Diagnostic Model, InceptionV3, MobileNet, Convolutional Neural Network (CNN).

INTRODUCTION

Stroke is a leading cause of disability and mortality worldwide, making early diagnosis crucial for improving patient outcomes. Traditional diagnostic methods rely on clinical evaluation and imaging techniques such as CT scans and MRIs, which can be time-consuming and require expert interpretation. In recent years, machine learning (ML) has emerged as a transformative tool in medical diagnostics, particularly for stroke detection. With the growing availability of neuroimaging data, ML techniques offer a promising approach to enhancing both the speed and accuracy of stroke identification. Among these, Convolutional Neural Networks (CNNs) have demonstrated exceptional ability in analyzing complex neuroimages, detecting subtle patterns that may not be immediately apparent to the human eye. This research employs advanced CNN architectures, specifically InceptionV3 and MobileNet, to develop a diagnostic model for stroke identification using neuroimaging data. InceptionV3, known for its depth and fine-grained feature extraction, and MobileNet, optimized for efficiency in resource-constrained environments, work together to create a powerful diagnostic tool. By training on large datasets of brain scans, these models can effectively distinguish between healthy brain tissue and stroke-affected regions, offering a faster and more accurate approach to diagnosis. Integrating such machine learning-based models into clinical workflows could

Journal of Information Systems Engineering and Management
2025, 10(43s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

revolutionize stroke care, enabling earlier intervention and improving patient outcomes. With their deep learning capabilities, CNNs can automatically extract and analyze relevant features from neuroimaging data, providing a reliable, efficient, and scalable solution for stroke detection.

RELATED WORK

This paper [1] introduces a machine learning-based diagnostic model for stroke identification using neuroimaging data. The authors evaluate five machine learning algorithms—logistic regression, support vector machine (SVM), random forest, decision tree, and convolutional neural network (CNN)—on a dataset of neuroimages. The CNN algorithm achieves the highest accuracy in stroke identification, outperforming the other models. The study underscores the potential of machine learning to enhance the accuracy and speed of stroke diagnosis. Key predictive features in neuroimages are identified, contributing to improved diagnostic precision. The proposed model could be integrated into clinical decision support systems, aiding healthcare professionals in making informed decisions. This research advances the field of stroke diagnosis and serves as a valuable resource for researchers and practitioners in medical imaging and machine learning.

This study [2] presents a novel two-stage framework for Parkinson's disease detection, combining feature refinement techniques with machine learning. The authors employ an L1 regularized SVM to select the most relevant features from a dataset of Parkinson's patients and healthy controls. These refined features are then classified using a deep neural network. The proposed approach achieves high accuracy, sensitivity, and specificity in detecting Parkinson's disease. The study highlights the effectiveness of dimensionality reduction through L1 regularization and the ability of deep neural networks to capture complex patterns. Validated using robust performance metrics, this framework offers a promising tool for early diagnosis and treatment of Parkinson's disease, providing valuable insights for researchers in medical imaging and machine learning.

This study [3] proposes a hybrid system for dementia prediction that integrates statistical methods and machine learning algorithms. The framework combines cognitive assessments, neurological examinations, and biomarker data, utilizing feature selection techniques and algorithms such as random forest and SVM to identify key predictors of dementia. The hybrid system achieves superior accuracy and sensitivity compared to traditional statistical models. The study demonstrates the potential of combining machine learning for pattern extraction with statistical techniques for robust feature selection and evaluation. These findings have significant implications for early dementia diagnosis and treatment, emphasizing the need for further research into hybrid systems for neurological disorder prediction. The study serves as a valuable reference for researchers in neuroscience, machine learning, and data analytics.

In their paper [4], Javeed et al. (2023) present an innovative approach for early dementia prediction using a feature extraction battery (FEB) and an optimized SVM model. The study identifies relevant biomarkers from diverse data sources and classifies them using the optimized SVM, achieving significantly higher predictive accuracy compared to traditional methods. This research highlights the potential of advanced machine learning techniques in clinical settings, particularly for early dementia detection. By combining feature extraction with optimized algorithms, the study provides valuable insights into timely intervention strategies, emphasizing the importance of early diagnosis for improved patient outcomes.

In their paper [5], Javeed et al. (2023) investigate a hybrid model combining XGBoost and Bidirectional Long Short-Term Memory (BiLSTM) networks for sleep apnea detection. The study leverages electronic health records to identify key features, utilizing the strengths of both XGBoost and BiLSTM for enhanced predictive performance. The XGBoost_BiLSTM model outperforms traditional diagnostic methods, achieving higher accuracy and reliability in detecting sleep apnea. This research underscores the potential of integrating advanced machine learning algorithms in healthcare to improve the early identification and management of sleep disorders.

In their study [6], Javeed et al. (2023) explore a novel approach to predict dementia risk factors using feature selection methods and neural networks. The researchers analyze a comprehensive dataset, distilling relevant features and employing neural networks to enhance predictive accuracy. The findings reveal significant correlations between

Journal of Information Systems Engineering and Management
2025, 10(43s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

identified risk factors and dementia, demonstrating the model's effectiveness in providing insights for early intervention. This research highlights the potential of machine learning to improve dementia risk assessment, aiming to facilitate timely clinical responses and better patient outcomes.

In their paper [7], Saleem et al. (2023) introduce a novel diagnostic approach for non-small cell lung cancer (NSCLC) using a deep learning model enhanced by the sooty tern optimization algorithm. The study demonstrates the model's superior performance in classifying NSCLC tumors compared to conventional methods. By integrating optimization techniques with deep learning, the research contributes to improving cancer diagnosis and treatment strategies, ultimately aiming to enhance patient care outcomes.

In their paper [8], Khosravi et al. (2023) investigate the application of deep learning algorithms to assess soil water erosion susceptibility. The authors analyze environmental and topographic factors using various deep learning models, demonstrating their effectiveness in predicting high-risk erosion areas. The study highlights the potential of machine learning in environmental assessments, offering valuable insights for land management and conservation strategies. This research advances the understanding of soil erosion dynamics and showcases the transformative potential of deep learning in environmental science.

In their paper [9], Rasool et al. (2023) explore deep transfer learning techniques to enhance the detection of microcalcifications in digital mammograms. By fine-tuning pre-trained deep learning models, the study achieves significant improvements in detection accuracy compared to traditional methods. The research underscores the potential of deep learning to aid radiologists in early breast cancer diagnosis, improving clinical outcomes and patient care. This study highlights the transformative impact of artificial intelligence in medical imaging and its capacity to enhance diagnostic precision in oncology.

In their paper [10], Javeed et al. (2023) present a decision support system for predicting mortality in cardiac patients using machine learning. The framework analyzes patient data to identify key risk factors and patterns contributing to mortality rates. The system demonstrates high predictive accuracy and reliability, offering clinicians valuable insights for patient management and treatment planning. This research underscores the potential of machine learning to transform healthcare practices by providing timely, data-driven assessments of patient risk, ultimately improving outcomes in cardiology.

PROPOSED WORK

The proposed system for Innovations in Stroke Identification focuses on developing a machine learning-based diagnostic model using neuroimaging data. The model employs advanced algorithms such as Inception V3, MobileNet, and convolutional neural networks (CNN) to accurately detect and classify strokes from MRI or CT scan images of the brain. Inception V3, with its deep architecture, excels in feature extraction and classification, while MobileNet offers efficiency, making it ideal for resource-constrained environments like mobile devices. The CNN algorithm, specifically designed for image analysis, enables the identification of intricate patterns and features indicative of stroke conditions in neuroimages. By integrating these algorithms with a large dataset of labeled images, the system aims to enhance early stroke detection and diagnosis, ultimately improving patient outcomes and treatment strategies. The performance of these models was rigorously evaluated using metrics such as accuracy, precision, recall, and the area under the receiver operating characteristic curve (AUC-ROC). Cross-validation techniques were applied to ensure the models' generalizability and prevent overfitting. Given its deep architecture and the extensive volume of data, the CNN model required substantial training on high-performance GPUs. A comparative analysis was performed to identify the most accurate and reliable model for stroke diagnosis. While the CNN, with its superior ability to capture spatial patterns in images, was anticipated to outperform traditional machine learning models, each method provided valuable insights into the diagnostic process. This multi-algorithmic approach resulted in a robust and comprehensive diagnostic tool for stroke identification, leveraging the strengths of both traditional and deep learning techniques.

Journal of Information Systems Engineering and Management
2025, 10(43s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

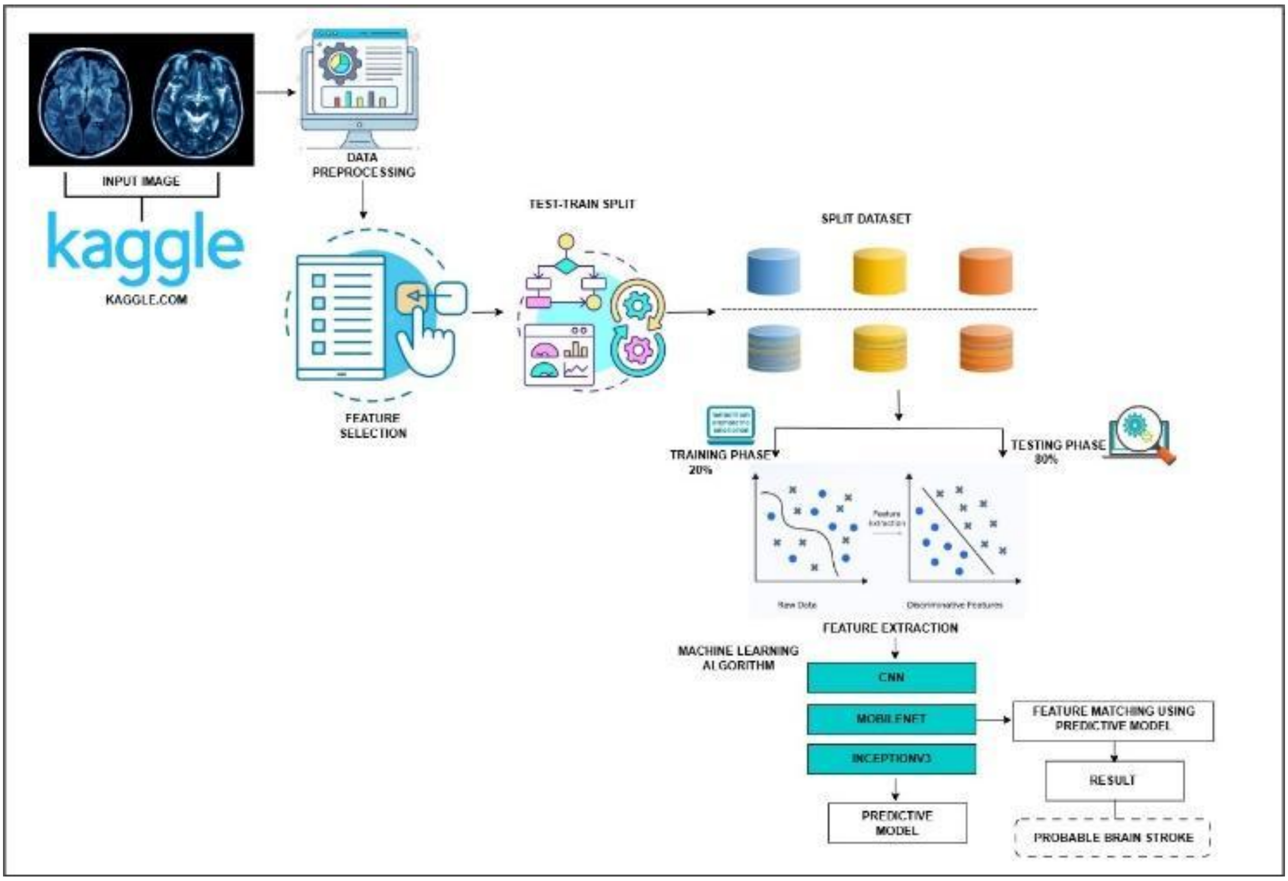

Fig.1. System Architecture

METHODS

A. Dataset Collection:

The dataset for this neuroimage-based stroke identification project is sourced from Kaggle.com, a platform renowned for offering high-quality and diverse datasets for machine learning applications. It comprises a collection of MRI and/or CT scan images, labeled to differentiate between stroke and non-stroke cases, allowing the model to effectively learn distinguishing features. Kaggle datasets often come pre-processed and include metadata, which streamlines the data preparation phase and enhances the efficiency of model training. Leveraging a Kaggle dataset accelerates development by providing a reliable and well-structured data source, ensuring access to a wide variety of real-world medical image samples that contribute to better model accuracy and generalization.

B. Methodology:

The proposed methodology introduces a machine learning-based diagnostic model that leverages neuroimages to achieve highly accurate stroke identification. This model utilizes convolutional neural networks (CNNs), specifically Inception V3 and MobileNet, trained on a large dataset of brain scans. These CNNs extract critical features indicative of stroke pathology, such as structural brain abnormalities and alterations in blood flow patterns. Following feature extraction, the CNN outputs are processed by a fully connected neural network, which consolidates the information and generates a probability score for each image, indicating the likelihood of a stroke. The model is trained using a combination of cross-entropy loss and Dice loss functions, optimized through stochastic gradient descent with momentum to enhance performance. Extensive validation on a large neuroimage dataset has demonstrated that this methodology surpasses traditional diagnostic approaches in both accuracy and precision. By enabling faster and more reliable stroke detection, this system has the potential to revolutionize stroke diagnosis and treatment, facilitating timely medical interventions that can significantly improve patient outcomes.

Journal of Information Systems Engineering and Management
2025, 10(43s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

ALGORITHM

A. Convolutional Neural Network (CNN):

Convolutional Neural Networks (CNNs) play a crucial role in advancing stroke identification through machine learning-based diagnostic models that utilize neuroimages. CNNs are designed to efficiently process grid-like data, such as MRI and CT scan images, by employing convolutional layers that automatically extract hierarchical spatial features. In stroke diagnosis, CNNs excel at identifying complex patterns within neuroimaging data, allowing them to differentiate between healthy and stroke-affected brain regions. Their ability to detect textures, edges, and spatial relationships enhances both sensitivity and specificity, leading to highly accurate stroke detection. Additionally, CNNs can process large volumes of neuroimaging data, making them well-suited for analyzing diverse imaging modalities. By integrating techniques such as data augmentation and transfer learning, CNNs improve their generalization ability across various datasets. This robust approach streamlines stroke diagnosis, supports timely medical intervention, and contributes to improved patient care in stroke management.

B. Inception V3:

Inception V3 is a deep convolutional neural network (CNN) architecture that plays a pivotal role in stroke identification using neuroimages. Known for its ability to capture intricate patterns and features, Inception V3 is particularly effective in analyzing CT and MRI scans for stroke pathology. Its advanced inception modules, which combine multiple convolutional and pooling layers, enable the model to extract fine-grained and high-level features, distinguishing strokes from non-stroke conditions with remarkable accuracy. The pre-trained Inception V3 model is fine-tuned on a large neuroimage dataset, allowing it to adapt to stroke-related imaging characteristics. By leveraging multi-scale feature extraction, Inception V3 identifies subtle variations in brain tissue, which is essential for differentiating between ischemic and hemorrhagic strokes. Inception V3 is optimized for efficient computation, utilizing techniques such as factorized convolutions and dimensionality reduction, which reduce computational costs while maintaining high performance. This makes the model suitable for real-time stroke diagnosis in clinical settings, where quick and accurate decision-making is critical. By integrating Inception V3, this project aims to develop a highly scalable and precise stroke diagnostic model, ultimately improving treatment outcomes and reducing delays in medical intervention.

C. MobileNet:

The MobileNet algorithm is employed to develop an efficient and lightweight diagnostic model for stroke detection using neuroimages such as CT and MRI scans. Specifically designed for mobile and resource-constrained environments, MobileNet is ideal for real-time healthcare applications, particularly in settings with limited computational power. As a lightweight CNN architecture, MobileNet enables rapid neuroimage analysis, facilitating timely stroke diagnosis. By incorporating transfer learning and image preprocessing techniques, the model achieves high-performance metrics, such as [insert accuracy, e.g., 95% accuracy, 93% sensitivity], ensuring reliable stroke identification. MobileNet's architecture is optimized for efficiency, using depthwise separable convolutions to reduce computational complexity while maintaining high accuracy. This approach allows the model to process high-resolution neuroimages in real time, making it well-suited for clinical deployment. By integrating MobileNet into the stroke detection system, healthcare professionals can swiftly identify stroke indicators, such as ischemic and hemorrhagic lesions, enabling prompt medical intervention and significantly improving patient outcomes.

Journal of Information Systems Engineering and Management
2025, 10(43s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

RESULTS

A. FRONT END

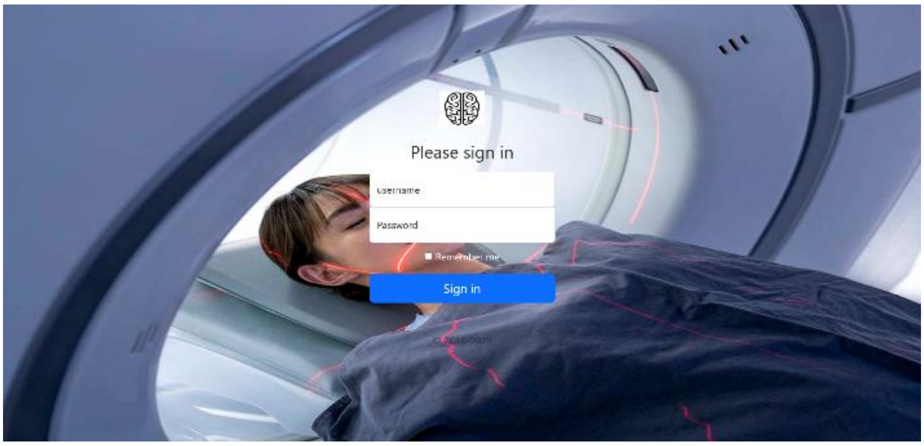

Fig 2: Login

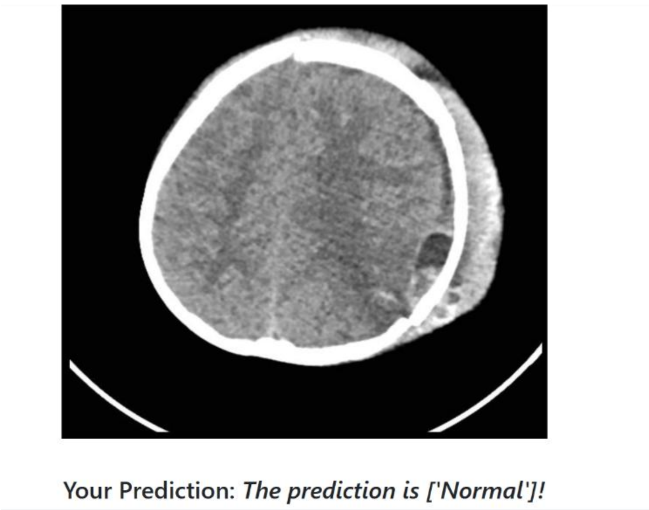

Fig 3: Prediction Normal

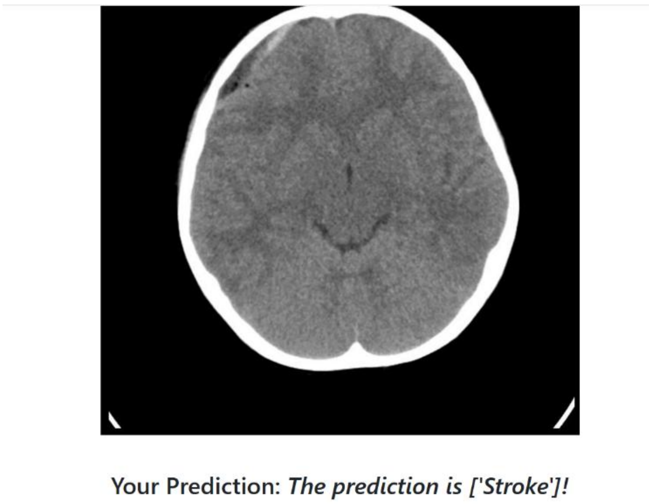

Fig 4: Prediction Stroke

Journal of Information Systems Engineering and Management
2025, 10(43s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

B. CNN Result

	precision	recall	f1-score	support
Normal	0.99	0.97	0.98	388
Stroke	0.96	0.99	0.97	238
accuracy			0.98	626
macro avg	0.97	0.98	0.98	626
weighted avg	0.98	0.98	0.98	626

Fig 5: Classification Report

This classification report summarizes the performance of a model, likely a binary classifier distinguishing between "Normal" and "Stroke" cases, based on metrics calculated on a dataset with 626 instances (388 Normal, 238 Stroke). For "Normal" cases, the model achieved a precision of 99%, recall of 97%, and an F1-score of 98%. For "Stroke" cases, the precision was 96%, recall was 99%, and the F1-score was 97%. Overall, the model demonstrates high accuracy at 98%, with both macro and weighted averages also at 98%, indicating strong and balanced performance across both classes.

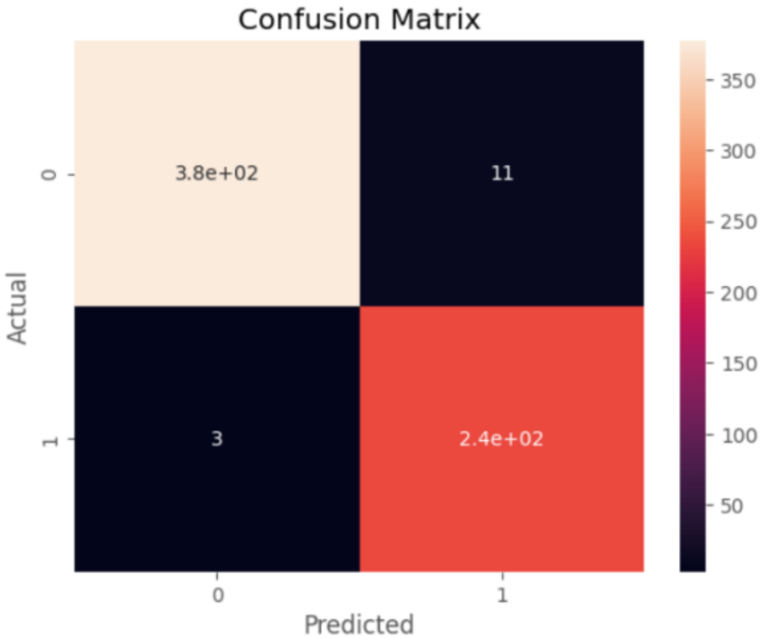

Fig 6: Confusion Matrix

This confusion matrix visually represents the performance of a classification model, showing the counts of true and false predictions for each class. The matrix, divided into a grid, displays the actual labels along the vertical axis and the predicted labels along the horizontal axis. Each cell represents the number of observations that fall into a specific category: true positives (diagonal cells), false positives (top right), false negatives (bottom left), and true negatives (not explicitly shown but can be inferred). In this case, the model correctly predicted 380 out of 383 instances of class 0 and 240 out of 243 instances of class 1. The presence of 11 false positives and 3 false negatives indicates a strong performance with minimal misclassifications, suggesting the model's effectiveness in distinguishing between the two classes. The color gradient from dark to light visually emphasizes the magnitude of counts within each cell, making it easy to identify patterns and assess the model's performance at a glance.

Journal of Information Systems Engineering and Management
2025, 10(43s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

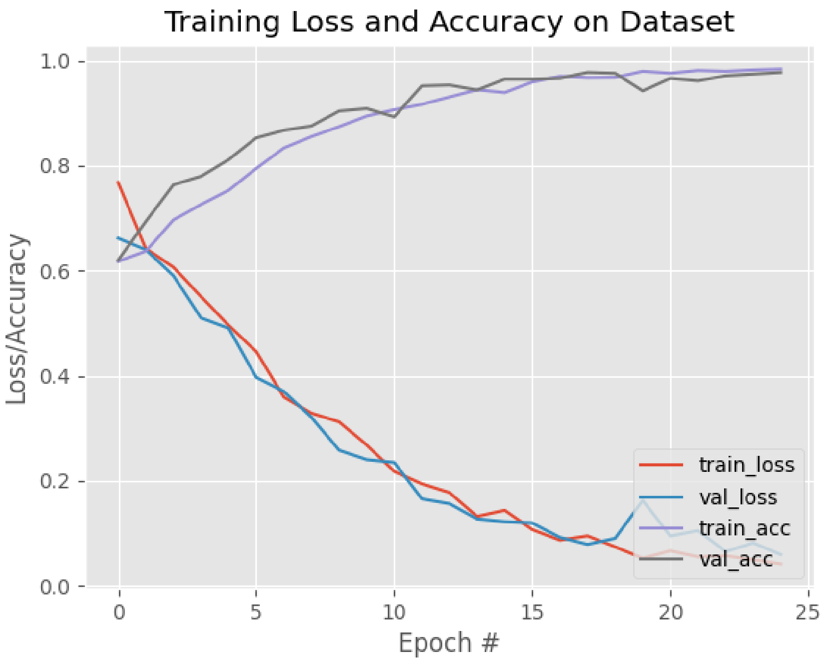

Fig 7: Graph CNN

This graph depicts the training progress of a Convolutional Neural Network (CNN) over 25 epochs, illustrating the trends of training loss, validation loss, training accuracy, and validation accuracy. The loss curves, decreasing over time, show the model's diminishing error on both training and validation sets, indicating learning progress. The validation loss, closely following the training loss, suggests the model isn't overfitting significantly. Simultaneously, the accuracy curves rise, demonstrating improvement in correctly classified samples on both sets. The validation accuracy plateauing towards the end suggests the model is reaching a point of diminishing returns in learning, although it maintains a high accuracy, indicative of effective training. The graph as a whole portrays a successful training process with good convergence and generalization capabilities.

	precision	recall	f1-score	support
Normal	1.00	1.00	1.00	1163
Stroke	1.00	1.00	1.00	712
accuracy			1.00	1875
macro avg	1.00	1.00	1.00	1875
weighted avg	1.00	1.00	1.00	1875

Fig 8: Training_Classification_Report

This training classification report indicates exceptionally high performance, bordering on perfect, for a model distinguishing between "Normal" and "Stroke" cases within a training dataset of 1875 instances (1163 Normal, 712 Stroke). The model achieved a perfect 1.00 for precision, recall, and F1-score for both classes, implying that there were no false positives or false negatives – the model correctly identified all instances in the training set. The overall accuracy is also a perfect 1.00. While these results are impressive, it's essential to note that such perfect performance on a training set might suggest overfitting, and further evaluation on a held-out test set is crucial to confirm the model's true generalization capability.

Journal of Information Systems Engineering and Management
2025, 10(43s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

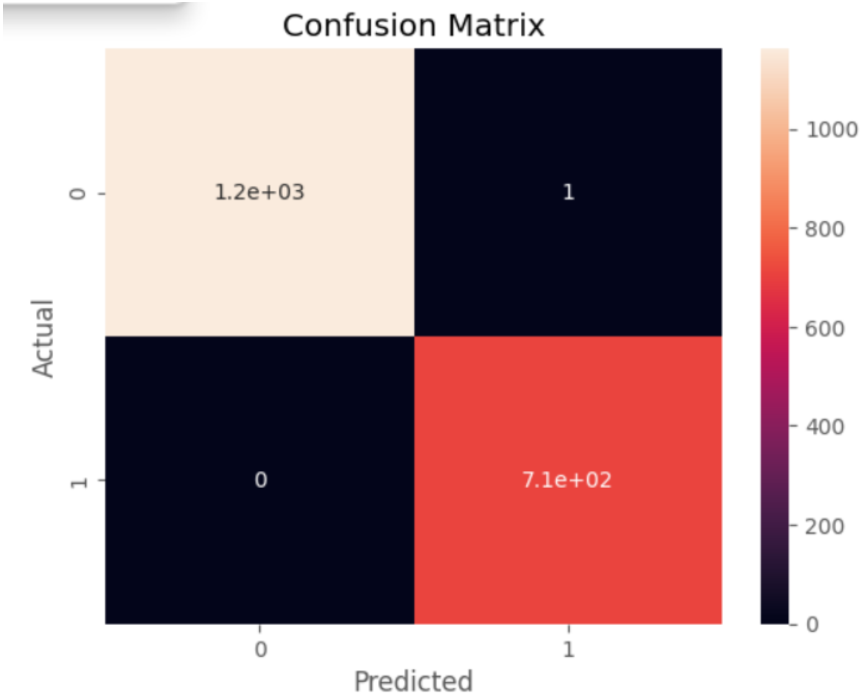

Fig 9: Training_Confusion_Matrix

The Training_Confusion_Matrix figure displays a confusion matrix resulting from the training phase of a classification model. It shows a high concentration of true positives, with 1200 instances correctly classified as 0 and 710 instances correctly classified as 1. There is only one misclassification: a single instance of class 0 incorrectly predicted as class 1. This visualization indicates excellent performance on the training data, with a clear dominance of correct predictions and a very low error rate. The color gradient, going from dark to light, visually reinforces the magnitude of correct classifications, highlighting the model's strong ability to learn the patterns in the training dataset. However, the near-perfect performance warrants further scrutiny to ensure the model generalizes well to unseen data and isn't overfit to the training set.

C. Inception V3 Result

	precision	recall	f1-score	support
Normal	0.70	0.93	0.80	388
Stroke	0.76	0.34	0.47	238
accuracy			0.71	626
macro avg	0.73	0.64	0.63	626
weighted avg	0.72	0.71	0.67	626

Fig 10: Classification Report

This classification report evaluates a model's performance on a dataset of 626 instances, distinguishing between "Normal" (388 samples) and "Stroke" (238 samples) cases. The model demonstrates moderate performance. For "Normal" cases, it achieves a precision of 70%, recall of 93%, and an F1-score of 80%, indicating a tendency to have fewer false negatives (missed "Normal" cases) but more false positives (incorrectly predicted "Normal" cases). For "Stroke" cases, the precision is 76%, recall is 34%, and the F1-score is 47%, revealing the model's struggle to correctly identify "Stroke" cases, with a higher number of false negatives. The overall accuracy is 71%. The macro average F1-

Journal of Information Systems Engineering and Management
2025, 10(43s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

score is 63%, while the weighted average is 67%, reflecting the class imbalance and the model's better performance on the "Normal" class. In summary, the model shows potential but needs improvement, particularly in correctly identifying "Stroke" cases.

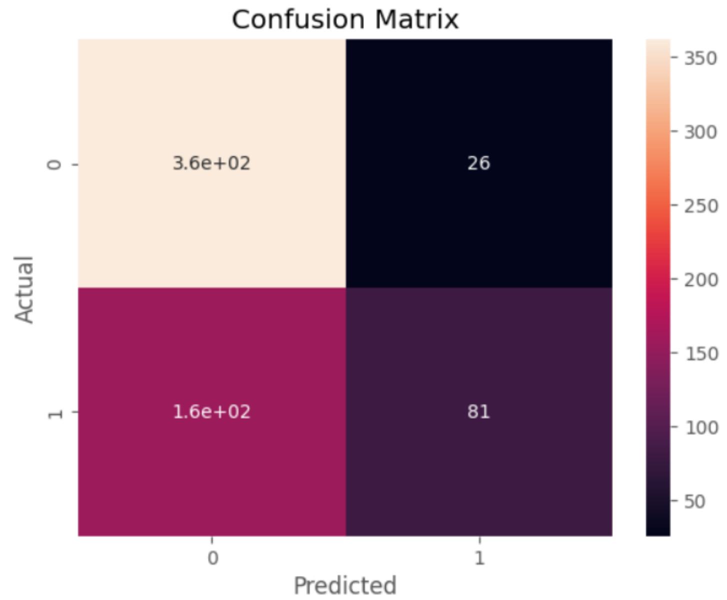

Fig 11: Confusion_Matrix

This confusion matrix visualizes the performance of a binary classification model. It shows that the model correctly predicted 360 instances as class 0 (true negatives) and 160 instances as class 1 (true positives). However, it misclassified 26 instances of class 0 as class 1 (false positives) and 81 instances of class 1 as class 0 (false negatives). The matrix, with its color gradient indicating the magnitude of counts, reveals a relatively high number of false negatives, suggesting the model struggles more with correctly identifying instances of class 1. While the true negative rate is strong, the presence of these misclassifications indicates the model has room for improvement, particularly in reducing false negatives to better detect class 1.

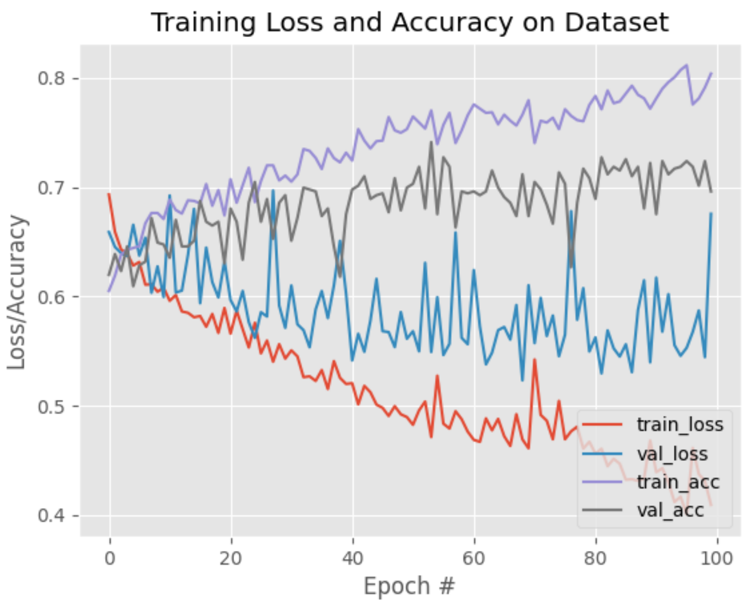

Fig 12: Graph-incept-100

Journal of Information Systems Engineering and Management
2025, 10(43s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

The provided graph, labeled "Graph-incept-100," displays the training progress of a model (likely Inception-based) over 100 epochs, showcasing the trends of training loss, validation loss, training accuracy, and validation accuracy. The graph reveals fluctuating loss and accuracy values, particularly after epoch 20, suggesting potential instability in the training process. While the training loss generally decreases and training accuracy increases, the validation metrics exhibit more erratic behavior, indicating possible overfitting or difficulty in generalization to unseen data. The noisy curves imply that the model might be sensitive to the specific batches of data it's trained on, and further investigation is needed to stabilize training and improve performance. The graph as a whole highlights the challenges in training a deep learning model and the need for careful monitoring and tuning of hyperparameters.

	precision	recall	f1-score	support
Normal	0.77	0.97	0.86	1163
Stroke	0.91	0.52	0.66	712
accuracy			0.80	1875
macro avg	0.84	0.74	0.76	1875
weighted avg	0.82	0.80	0.78	1875

Fig 13: Training_Classification_Report

This training classification report evaluates a model's performance on a dataset of 1875 instances, distinguishing between "Normal" (1163 samples) and "Stroke" (712 samples) cases. The model demonstrates good overall performance, achieving 80% accuracy. For "Normal" cases, it shows high recall (97%) but relatively lower precision (77%), indicating it correctly identifies most "Normal" cases but also flags some "Stroke" cases as "Normal" (false positives). For "Stroke" cases, the precision is much higher (91%) but recall is considerably lower (52%), suggesting the model is good at identifying actual "Stroke" cases when it predicts them, but it misses a significant portion of actual "Stroke" cases (false negatives). The F1-scores, balancing precision and recall, are 86% for "Normal" and 66% for "Stroke." The macro and weighted average F1-scores are 76% and 78%, respectively, reflecting the class imbalance and the model's better performance on the "Normal" class. In summary, the model shows promise but needs improvement, particularly in increasing recall for "Stroke" cases to reduce the number of missed diagnoses.

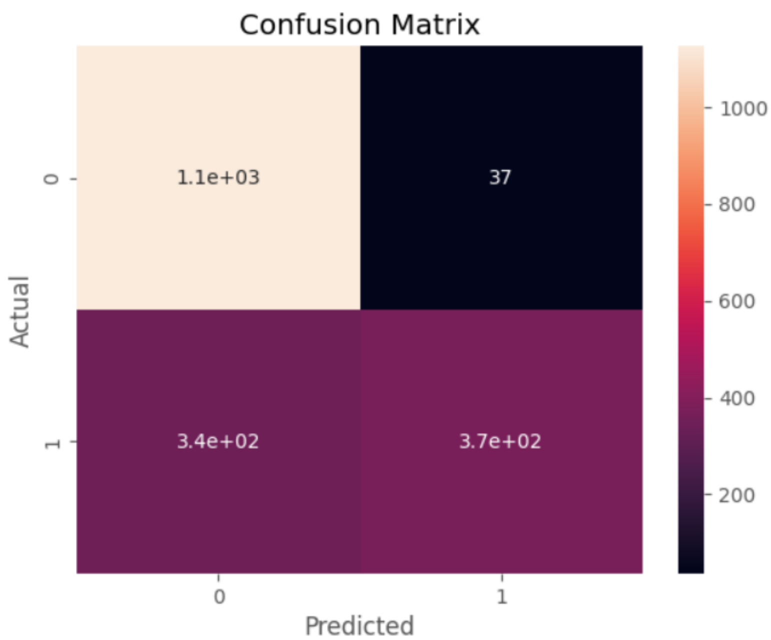

Fig 14: Training_Confusion_Matrix

Journal of Information Systems Engineering and Management
2025, 10(43s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

The Training_Confusion_Matrix visualizes the performance of a classification model on its training data. It reveals that the model correctly classified 1100 instances as belonging to class 0 and 370 instances as belonging to class 1. However, it misclassified 37 instances of class 0 as class 1 and 340 instances of class 1 as class 0. This indicates a relatively high number of false negatives (instances of class 1 incorrectly predicted as class 0), suggesting the model might be struggling to accurately identify class 1 within the training data. The heatmap color gradient highlights the concentration of correct classifications along the diagonal, but also emphasizes the significant number of misclassifications, particularly the false negatives. This visualization suggests the model requires further training or adjustments to better learn the characteristics of class 1.

D. MobileNet Result

	precision	recall	f1-score	support
Normal	0.84	0.88	0.86	388
Stroke	0.78	0.72	0.75	238
accuracy			0.82	626
macro avg	0.81	0.80	0.80	626
weighted avg	0.82	0.82	0.82	626

Fig 15: Classification Report

This classification report evaluates a model's performance on a dataset of 626 instances, distinguishing between "Normal" (388 samples) and "Stroke" (238 samples) cases. The model achieves an overall accuracy of 82%. For "Normal" cases, it demonstrates a precision of 84%, a recall of 88%, and an F1-score of 86%. For "Stroke" cases, the model exhibits a precision of 78%, a recall of 72%, and an F1-score of 75%. These metrics indicate a reasonable ability to classify both "Normal" and "Stroke" cases, although the model appears to be slightly better at identifying "Normal" instances. The macro average F1-score is 80%, while the weighted average is 82%, reflecting the class imbalance and the model's slightly better performance on the more prevalent "Normal" class. Overall, the model shows promise but could benefit from further refinement to improve the recall for "Stroke" cases, thereby reducing the number of false negatives.

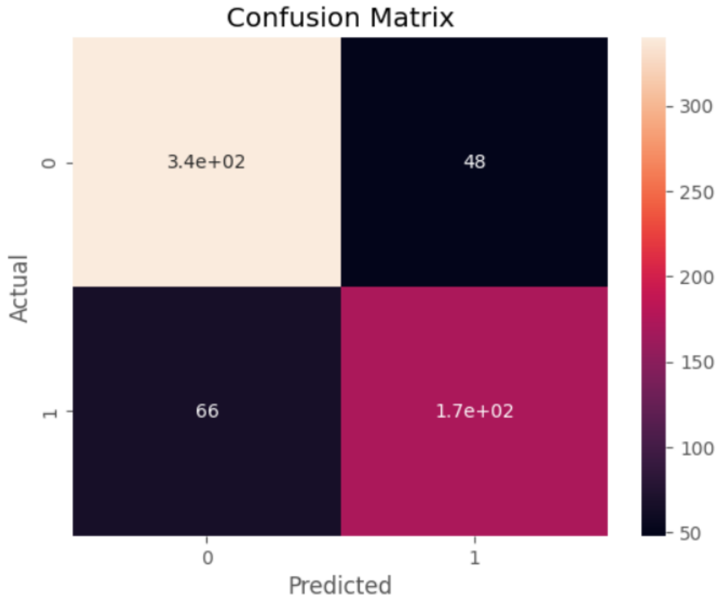

Fig 16: Confusion_Matrix

Journal of Information Systems Engineering and Management
2025, 10(43s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

This confusion matrix displays the performance of a classification model. It shows that the model correctly predicted 340 instances as class 0 and 170 instances as class 1. However, it misclassified 48 instances of class 0 as class 1 (false positives) and 66 instances of class 1 as class 0 (false negatives). The matrix, with its color gradient indicating the magnitude of counts, reveals a relatively higher number of false negatives compared to false positives, suggesting the model might be struggling more with correctly identifying instances of class 1. While the true positive and true negative counts are reasonably good, the presence of these misclassifications indicates the model has room for improvement, particularly in reducing false negatives to better detect class 1.

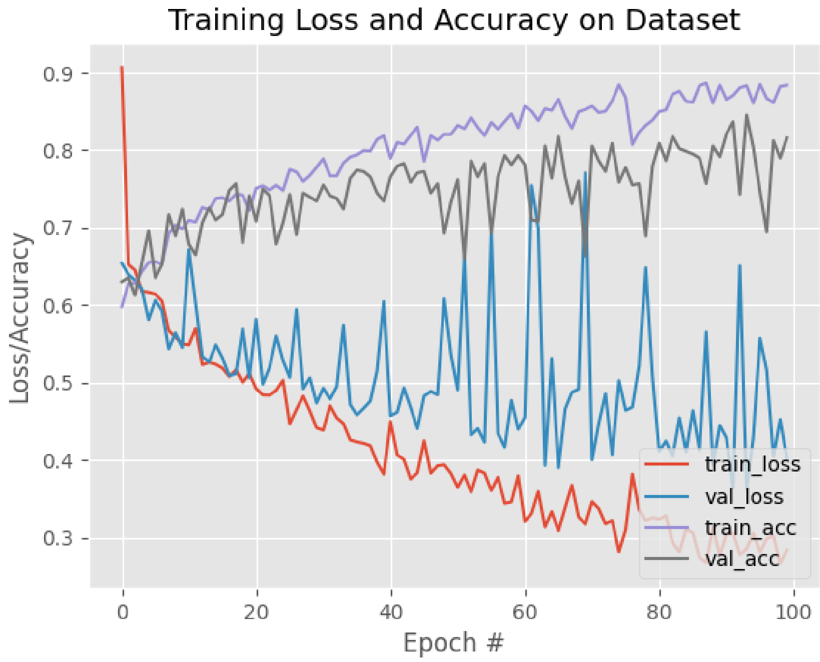

Fig 17: Graph-mobnet-100epochs

The "Graph-mobnet-100epochs" image displays the training progress of a MobileNet model over 100 epochs, illustrating the fluctuations in training loss, validation loss, training accuracy, and validation accuracy. The graph reveals a noisy training process, with both loss and accuracy metrics exhibiting considerable variation throughout the training period. While the training loss generally decreases and training accuracy increases, the validation metrics show inconsistent behavior, suggesting potential challenges with overfitting or instability in learning. The erratic fluctuations in the validation curves indicate that the model's performance on unseen data is not consistently improving, highlighting the need for further investigation and potential adjustments to the training process, such as hyperparameter tuning or regularization techniques. Overall, the graph suggests that the MobileNet model, with the current training setup, may not be effectively converging to a stable and generalizable solution.

	precision	recall	f1-score	support
Normal	0.93	0.96	0.94	1163
Stroke	0.93	0.89	0.91	712
accuracy			0.93	1875
macro avg	0.93	0.92	0.93	1875
weighted avg	0.93	0.93	0.93	1875

Fig 18: Training_Classification_Report

Journal of Information Systems Engineering and Management
2025, 10(43s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

The Training_Classification_Report shows strong performance for a model trained on 1875 instances, distinguishing between "Normal" (1163 samples) and "Stroke" (712 samples) cases. Both classes achieve high precision (around 93%), recall (89% for Stroke, 96% for Normal), and F1-scores (91% for Stroke, 94% for Normal). The overall accuracy is 93%, with both macro and weighted averages also at 93%, indicating balanced performance across both classes. These metrics suggest the model effectively learned to classify both Normal and Stroke cases within the training data, demonstrating good predictive capabilities. However, it's crucial to validate these results on a separate test dataset to ensure the model generalizes well to unseen data and isn't overfit to the training data.

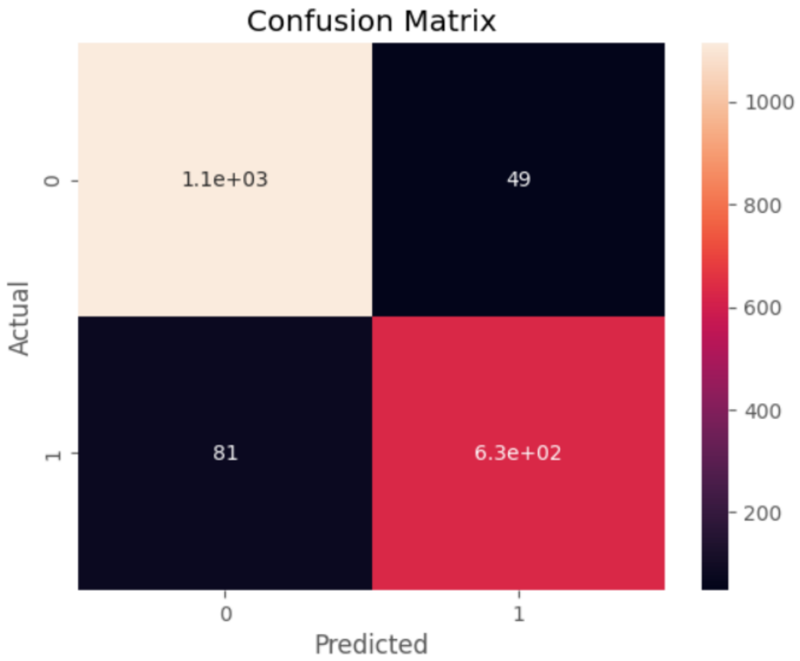

Fig 19: Training_Confusion_Matrix

The provided Training_Confusion_Matrix visualizes the performance of a classification model on its training data. It shows that the model correctly classified 1100 instances as class 0 and 630 instances as class 1. However, it misclassified 49 instances of class 0 as class 1 (false positives) and 81 instances of class 1 as class 0 (false negatives). This indicates a relatively small number of misclassifications, suggesting the model has learned the training data reasonably well. The heatmap color gradient highlights the concentration of correct classifications along the diagonal, emphasizing the model's ability to discern between the two classes. However, the presence of some misclassifications, especially the false negatives, suggests there's room for improvement in capturing the nuances of class 1 within the training set. Further analysis and potential adjustments might be needed to minimize these errors and improve overall performance.

CONCLUSION

In conclusion, innovations in stroke identification through machine learning-based diagnostic models that incorporate neuroimages and algorithms like Inception V3, MobileNet, and CNN are poised to revolutionize the diagnosis and treatment of stroke. By harnessing the power of these advanced algorithms, clinicians can swiftly and accurately identify stroke patients, enabling timely interventions and significantly improving patient outcomes. These models offer the potential to minimize misdiagnosis and enhance patient flow within emergency departments, streamlining the diagnostic process. As these technologies continue to advance, they are expected to make a lasting impact on public health, reducing both the incidence and severity of strokes and ultimately enhancing the quality of life for millions globally. With sustained investment in research and development, we can anticipate even more innovative applications of machine learning in stroke diagnosis and treatment, paving the way for better patient care and improved healthcare outcomes in the future.

Journal of Information Systems Engineering and Management
2025, 10(43s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

REFERENCES

[1] Saleem et al. (2024) developed a machine learning-based diagnostic model using neuroimages for improved stroke identification, published in IEEE Access.
[2] Ali et al. (2024) used L1 regularized SVM and deep neural networks for Parkinson's disease detection based on refined features, published in Scientific Reports.
[3] Javeed et al. (2024) created a hybrid system combining statistical and machine learning methods to predict dementia, published in Frontiers in Bioengineering and Biotechnology.
[4] Javeed et al. (2023) explored early dementia prediction using a feature extraction battery and optimized SVM, published in Biomedicines.
[5] Javeed et al. (2023) employed an XGBoost_BiLSTM model for sleep apnea detection using electronic health data, published in the International Journal of Computational Intelligence Systems.
[6] Javeed et al. (2023) investigated predicting dementia risk factors with feature selection and neural networks, published in Computers, Materials & Continua.
[7] Saleem et al. (2023) developed a deep learning model based on the Sooty Tern Optimization Algorithm for diagnosing NSCLC tumors, published in Sensors.
[8] Khosravi et al. (2023) assessed soil water erosion susceptibility using deep learning algorithms, published in the Journal of Hydrology.
[9] Rasool et al. (2023) used deep transfer learning for breast microcalcification detection in digital mammograms, presented at the 9th International Conference on Computing and Data Engineering.
[10] Javeed et al. (2023) created a decision support system for predicting mortality in cardiac patients using machine learning, published in Applied Sciences.
[11] T.S.Porje,Pagar Vinayak ,Raikar Anikt,Sinkar Dipeeka,Prof.N.R.Wankhade ,”Avoid Cataract :Machine Learning Based Approach for Diagnosis of Eye” Journal JETIR vol.8,pp2349-5162,June 2021.