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Cloud-Based Big Data Solutions for Healthcare Information Systems: Integrating AI, Data Security, and Alzheimer's Disease Diagnosis

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Abstract

Alzheimer's disease (AD) is a neurodegenerative condition that needs early and correct diagnosis for successful intervention. The goal of this work is to automate the diagnosis of Alzheimer's from MRI scans using a deep learning model that is a combination of LSTM-GRU and to encrypt patient data with AES encryption. Current techniques like SVM, CNN, and Random Forests have limitations when dealing with sequential data, overfitting, and weak generalization. The suggested framework combines both spatial and temporal information from MRI scans, overcoming these limitations by employing LSTM for temporal analysis and GRU for computational efficiency, while AES encryption provides data security. The procedure involves data collection, pre-processing with Z-score normalization, safe storage, classification using the hybrid model, and performance evaluation. The model achieved an accuracy of 99.20%, precision of 99.30%, recall of 99.10%, and F1-score of 99.20%, which is indicative of its viability for use in real-life clinical practice. Future improvement opportunities include the application of transfer learning and real-time data processing.

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Keywords

Alzheimer's Disease, Hybrid LSTM-GRU Model, AES Encryption, MRI Scans, Secure Data Storage, Cloud Storage.

Introduction

Alzheimer is one of the common cognitive diseases that impair elderly that needs effective intervention and care. By identifying structural changes in brain, using medical imaging especially, MRI scans play a major role in diagnosis of Alzheimer (1).

Conventional diagnosis via expert manual review of MRI images is usually time-consuming and prone to human error (2). The proposed new framework attempts to revolutionize the diagnostic process using a machine learning approach in order to facilitate automation of the diagnosis of Alzheimer's disease from MRI scans with earlier and more accurate outcomes for assistance in early-stage diagnosis.

Several methods have been proposed to deal with Alzheimer's detection from MRI data based on various machine learning and image processing techniques. SVM, CNN, and Random Forests have been employed in classification problems (3). Though SVM and CNN-based approaches exhibit good performance in feature extraction and classification, they are limited due to their inability to handle sequential data and learn the temporal patterns in the course of the disease (4). Second, present models are prone to overfitting, generalize poorly between datasets, and require large, annotated training sets in order to function optimally (5). These limitations confine their scalability and robustness in real-world clinical settings.

The suggested framework addresses such limitations by incorporating a hybrid LSTM-GRU model that captures spatial and temporal aspects in MRI scans (6). The LSTM part represents the temporal interdependencies in the data, which are crucial to analyse the disease development over time, and the GRU part makes the model more efficient by resolving problems of vanishing gradients (7). This hybrid approach improves classification performance more effectively processing structural and sequential data (8). In addition, the proposed framework has added AES encryption for secure storage of data so it can pass healthcare data safety regulations while maintaining system performance (9). This twofold focus on model performance and security differentiates the proposed framework from existing techniques (10).

The innovation of the current research is its potential to integrate deep learning architectures processing both the spatial and temporal information of MRI data (11), providing a level of accuracy and reliability not previously available for Alzheimer's diagnosis (12). Through solving the limitations of conventional methods and adding secure data management (13), the framework presents an end-to-end solution for automated, secure (14), and scalable detection of Alzheimer's(15). The generalizability of the hybrid LSTM-GRU model across various datasets and its usability in actual clinical settings are factors that render it a great leap in the use of medical imaging and machine learning for clinical applications (16).

Objectives

- ✓ Evaluate the performance of the suggested framework for automatic diagnosis of Alzheimer's disease from MRI scans through a hybrid LSTM-GRU deep learning model with the purpose of improving early and precise detection of the disease.
- ✓ Utilize MRI scan information symbolizing different levels of Alzheimer's disease, different classes, to train and evaluate the suggested model.
- ✓ Apply the hybrid model of LSTM and GRU to identify spatial as well as temporal dependencies between MRI scan data for enhanced classification and the capability to examine sequential shifts in the advancement of diseases.
- ✓ Incorporate AES encryption to safeguard the secure storage and protection of sensitive patient information, ensuring continued compliance with healthcare data security policies and maintaining system performance.

The research paper examines the use of cloud computing in health, targeting cloud-enabled system advantages and challenges as well as SaaS offerings (17). It elucidates several models for healthcare clouds, how they are structured (18), and how data mining techniques are applied to uncover insights from big health data (19). The study targets the integration of cloud-enabled healthcare systems (20), highlighting the possible advantages and issues involved with this technology in the health industry (21). It elaborates on the creation of SaaS specifically for healthcare (22), which is meant to evolve with the changing demands of physicians and patients globally (23). The paper reviews different models of healthcare clouds and architectures, including top providers offering SaaS offerings that enable health practitioners (24).

The paper talks about the revolutionary potential of big data in the healthcare sector, with its potential to transition from reactive to proactive healthcare (25), which can save costs and drive economic growth (26). It also talks about the paramount security and privacy concerns that emerge as the sector increasingly depends on big data with increased threats and vulnerabilities (27).

The healthcare sector is witnessing a massive growth in the volume of data as a result of the digitization of health records, which results in higher complexity (28), diversity, and timeliness of data (29). There is an urgent need for proactive healthcare and wellness strategies to meet growing healthcare costs and health insurance premiums (30).

Big data is viewed as a revolutionary solution that can reduce healthcare costs while enhancing care processes (31), delivery, and management (32). Privacy and security threats are significant areas of concern within the healthcare industry with increased adoption of big data (33), and forthcoming dangers and threats hold enormous implications (34).

Problem Statement

The research work (35) emphasize the need for advanced preclinical models of Alzheimer's disease (AD) because of the breakdown of a major proportion of clinical development programs (36). They refer to the application of computer-based modelling and simulation for the understanding of disease progression as well as the facilitation of drug discovery(37).Chart the application of big data in AD research across 38 studies from 2010 to 2015 (38). Their results are centred on main areas including AD diagnosis (39), conversion prediction from MCI to AD (40), and the application of datasets like electronic health records (41), where logistic regression and support vector machines were the most frequently used methods (42).

Some glaring challenges remain despite all the recent advances in applying computational methodologies and big data into Alzheimer's disease (AD) research (43). First, the heterogeneity of data sources, from imaging and genomics to clinical records and cognitive tests (44), impedes data integration and the consequent building of rigorously predictive modeling studies. Besides (45), many machine learning methodologies are simply not generalizable over populations (46), compounded by the fact that the datasets they use tend to be either biased or simply too restricted (47). Defining the variable dynamic temporal progression of AD, including prodromal onset through stages like mild cognitive impairment (MCI), is seldom well modeled by current means (48). As such, early and precise prediction of AD onset and progression is beyond just delayed (49), hence calling for a more holistic, interpretable, and scalable big data-driven methodology in AD research (50).

Proposed Methodology

The methodology describes the process for Alzheimer's disease classification based on MRI scans. It begins with Data Collection, in which MRI scans corresponding to four phases of Alzheimer's disease (No Impairment, Very Mild Impairment, Mild Impairment, and Moderate Impairment) are collected. It follows with the step of Data Pre-processing in which the data is normalized and missing values are handled to make it consistent and accurate.

Once pre-processing is completed, the data is safely stored using AES Encryption for data security and protection. The encrypted data is then utilized in the Classification phase, in which a hybrid deep learning architecture consisting of LSTM and GRU is employed in the classification operation. The output of the model is two categories: Present or Not Present, representing whether or not Alzheimer's is identified within the MRI scan. The last step is Performance Evaluation, where the performance of the model is evaluated with multiple performance metrics such as accuracy, precision, and recall. This validates the reliability of the model and its potential clinical use in Alzheimer's diagnosis in Figure 1.

Data Collection

Data collection for the proposed framework is MRI scan data for Alzheimer's disease, and the dataset contains four distinct classes. The classes represent various stages of Alzheimer's progression, ranging from mild cognitive impairment (MCI) to severe Alzheimer's. MRI data is obtained using sophisticated imaging techniques to obtain high-quality scans that can extract useful features for the identification of neurological conditions.

The information gathered includes brain structure images, which are essential in the determination of the severity of the disease. The information is stored safely in a cloud storage facility to facilitate easy access for future analysis and processing while maintaining privacy and adhering to healthcare data security standards. The information forms the foundation of the classification model, which will determine the presence or absence of Alzheimer's disease.

Preprocessing

Z-Score Normalization

Normalization is a method that is applied to standardize the range of the features. Z-score normalization, or standardization, scales the data so that it has a mean of 0 and a standard deviation of 1. In mathematical expression,

$$Z = \frac{X-\mu}{\sigma} \quad .....(1)$$

where, Z the normalized value, $X$the original value, μ the mean feature, σ the standard deviation feature.

This allows every feature in the dataset to have a mean of 0 and a standard deviation of 1, and thus the data is ready to be used with machine learning algorithms that are feature scaling sensitive, like LSTM and GRU.

Handling Missing Data

Missing data is a common issue in datasets. Imputation is the act of filling missing values with predicted values based on available data. There are various imputation methods, and some of these include mean or median imputation.

For a feature$X$missing values, the imputed value X_{imputed} is

$$X_{\text{imputed}} = \frac{\sum_{i=1}^{n} x_i}{n} \text{....(2)}$$

Where, X_i the observed feature value,n is the no of not missing values of feature. Also, median imputation is used as,

$$X_{\text{imputed}} = \text{median}(X) \text{...(3)}$$

This can be used as replacement of missing values in median of feature.

Secure Data Storage

Secure storage of data within the suggested paradigm is achieved by utilizing Advanced Encryption Standard (AES) to safeguard sensitive patient information, maintaining confidentiality and compliance with legislation such as HIPAA. Pre-processed MRI scan data is encrypted prior to being stored in a secure cloud storage, maintaining data security and integrity. AES encryption gives confidence that the data is secure from unauthorized usage, whereas cloud storage offers scalable and reliable access. The encrypted data can only be accessed by authorized personnel who possess decryption keys. Such safe storage mechanism ensures the patient information throughout the complete life cycle of the analysis.

Classification Using LSTM and GRU

The workflow of classification process in the diagram utilizes a combined deep learning model of GRU and LSTM networks. LSTM particularly is utilized to learn long-term dependencies within sequential data using the application of gates such as the forget gate, input gate, and output gate in a bid to control the flow of information.

It is better suited to time-series or sequential data applications, such as predicting Alzheimer's stages from MRI scans. GRU, on the other hand, simplifies LSTM by employing fewer gates (update and reset gates) at the cost of more computational efficiency in contrast to its ability to detect robust sequential patterns. LSTM-GRU strategy combination has the strengths of both models combining to effectively classify MRI data at various stages of Alzheimer's disease.

The addition of LSTM capacity for memory and GRU optimal learning capacity allows this model to be perfectly adept at handling high-level dynamic sequence data with high accuracy.

LSTM Classification

LSTM networks are designed to learn long dependencies and learn sequential patterns. Forget Gate, Input Gate, Output Gate, and Cell State are the major gates of LSTM. The basic LSTM update equations are:

a. ***Forget gate:*** Forget gate $f_t$determines which information from previous cell should be left out.

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \text{...(4)}$$

where, σ is sigmoid activation function, W_f is weight matrix for forget gate,h_{t-1} is previous hidden gate, x_t is current output, b_f is bias term.

b. ***Input gate:*** The input gate controls how much information has to be added to cell state.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \text{....}\textit{(5)}$$

Where, W_i is weight matrix for input gate, $b_i$is bias term.

c. ***Candidate Cell State:*** $\tilde{C}_t$creates new potential information to be stored in cell state.

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \text{...}\textit{(6)}$$

d. ***Update Cell State:*** The cell stateC_t is updated by combining the previous cell state, forget gate, and candidate cell state.

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \text{....}\textit{(7)}$$

e. ***Output Gate:*** $o_t$control the part of the cell state which should be output as hidden state.

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \text{...}\textit{(8)}$$

f. ***Hidden State:*** is calculated as,

$$h_t = o_t * \tanh(C_t)....(9)$$

GRU Classification

GRU reduces the LSTM architecture to fewer gates: Update Gate and Reset Gate. The update gate determines how much of the past state should be preserved, and the reset gate determines how much of the past memory should be forgotten.

a. ***Update Gate***: $z_t$decides how much of previous hidden state has to be kept.

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t] + b_z)....(10)$$

b. ***Reset Gate:*** controls how much of previous hidden state has to be forgotten.

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t] + b_r)....(11)$$

c. ***Candidate Hidden State:***$\tilde{h}_t$is calculated using the reset gate.

$$\tilde{h}_t = \tanh(W_h \cdot [r_t * h_{t-1}, x_t] + b_h)...(12)$$

d. ***Update the Hidden State:*** The final hidden stateh_t is updated by combining previous hidden state with candidate state, weighed by update gate.

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t...(13)$$

Results and Discussion

The outcomes acquired from the proposed framework for classifying Alzheimer's disease, using the hybrid LSTM-GRU model, are measured against common metrics like accuracy, precision, recall, F1-score, and confusion matrix.
These are used to give a complete assessment of how well the model predicts whether a patient has Alzheimer's disease or not based on the MRI scan input.

Confusion Matrix and Performance Metrices Graph

In this confusion matrix, the True Positive (TP) is 633, which is the number of accurately predicted "Present" (Alzheimer's disease present) instances. The True Negative (TN) is 635, which is correctly predicted "Not Present" instances. The False Positive (FP) is 5, where "Present" was predicted by the model when it should have been "Not Present." The False Negative (FN) is 6, where the model was unable to detect Alzheimer's presence. Overall, the model is extremely good at classifying both "Present" and "Not Present" classes.

The performance metrices, show the classification metrics of Alzheimer disease detection and presents its accuracy, precision, recall and F1-score. It gives an accuracy of 99.20%, showing the predictions were correct. A precision of 99.30% demonstrates the model’s ability to reduce false positives.

Figure.1 Overall Proposed Architecture

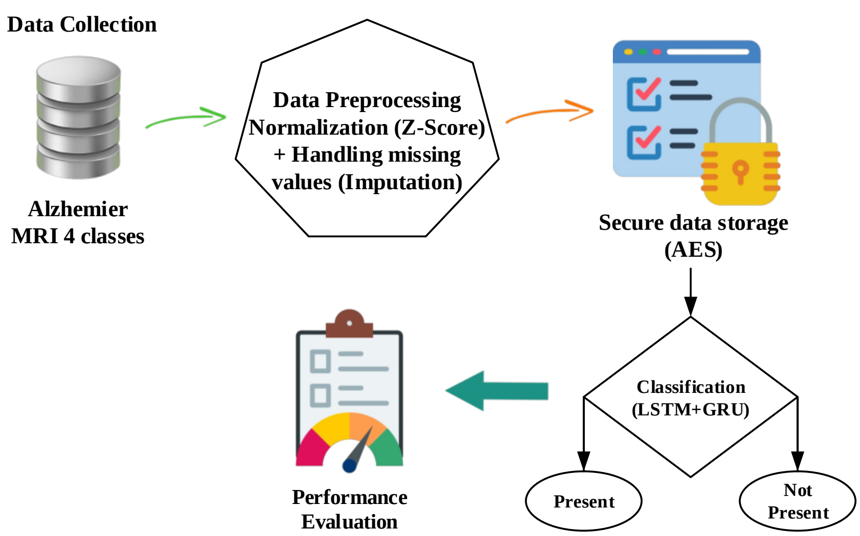


Figure.2 Hybrid Architecture (LSTM+GRU)

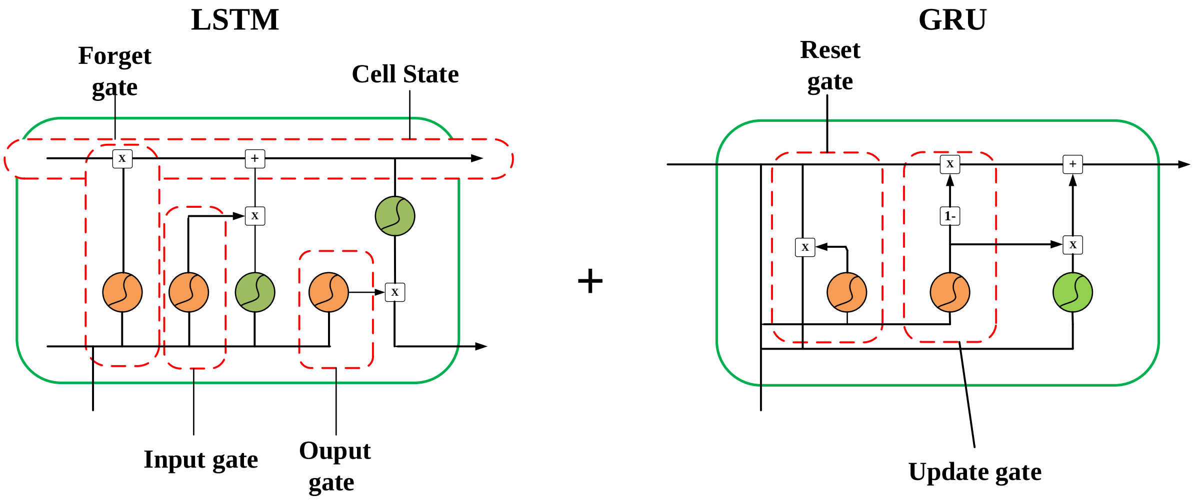


Figure.3 Confusion Matrix

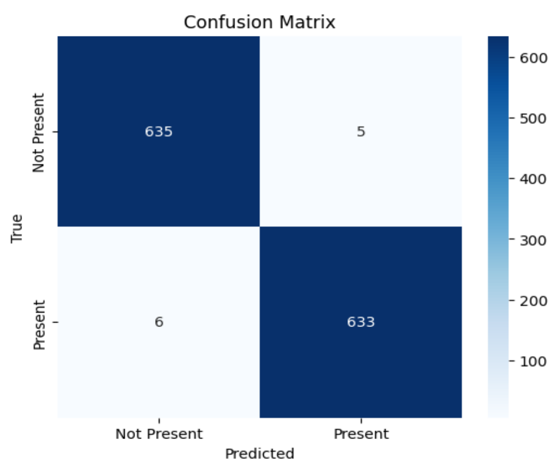


Figure.4 Performance Metrices

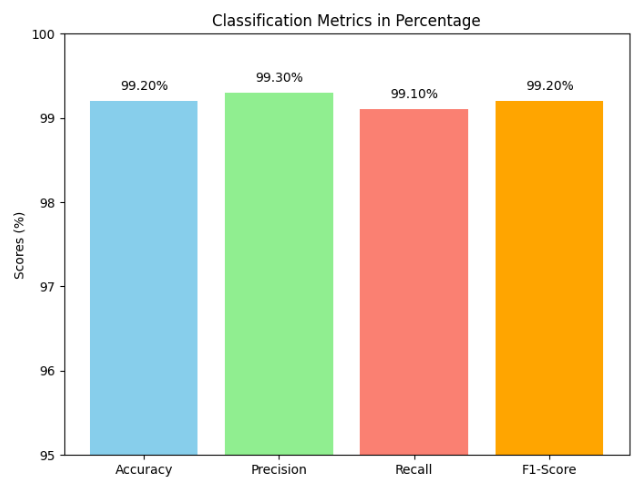
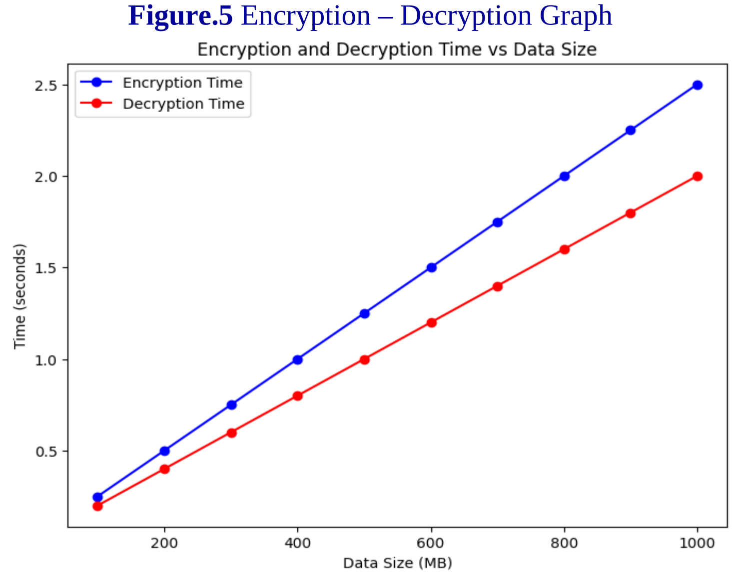


Figure.5 Encryption – Decryption Graph



In the same manner, a recall of 99.10% indicates that most instances of the presence of Alzheimer's were captured. Finally, the F1-score of 99.20% shows a good balance in the model's performance such that both precision and recall are in good proportion. These outcomes demonstrate the high performance of the model in classifying Alzheimer's disease.

The graph illustrates the linear growth in both encryption and decryption time with increasing data size. For example, when the data size is 200 MB, encryption consumes around 0.5 seconds, and decryption consumes 0.4 seconds. When the data size is 1000 MB, encryption time increases to around 2.4 seconds, and decryption time increases to 2.0 seconds. This shows that AES encryption grows proportionally with data size, having the same time complexity.

Conclusion and Future Enhancement

The proposed framework demonstrates the effective application of machine learning, i.e., the hybrid LSTM-GRU model, in Alzheimer's disease classification from MRI images. The result demonstrates high performance with accuracy (99.20%), precision (99.30%), recall (99.10%), and F1-score (99.20%), which confirm the capability of the model for early and accurate diagnosis. Additionally, the use of AES encryption ensures secure handling of confidential healthcare information as per regulatory compliance. These results confirm the readiness of the framework for use in actual clinical settings for the diagnosis of Alzheimer's.Future studies can involve generalizing the ability of the model by adding other varied datasets to remove biases in current training sets. Other sophisticated techniques like transfer learning from large imaging datasets can also optimize accuracy, especially in heterogeneous patient groups.

Incorporation of real-time data analysis and a more extensive model with other cognitive states would also increase the scope of the framework. Additional optimization of AES encryption to enable quicker processing of data without compromising security would further increase system efficiency. Lastly, research on cloud-based deployment of models can bring scalability to offer wider access to healthcare institutions across the world.

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