HYBRID DEEP LEARNING MODEL USING RESIDUAL ATTENTION AND BILSTM FOR ACCURATE ISCHEMIC HEART DISEASE CLASSIFICATION

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***Abstract*—Ischemic heart disease remains a major global health issue, making it important to develop accurate and reliable diagnostic methods. This study presents HRAE–LSTM, a deep learning model that examines patient health data to enhance prediction accuracy. Bidirectional LSTM layers examine data in both directions to identify issues during training, while the remaining connections allow the model to learn and avoid issues, as well as a strategy for directing attention to the most relevant aspects of the information. Missing data is handled by the model using K-Nearest Neighbors (KNN) imputation. In order to make educated guesses about any missing data, it finds similar patient records.The model training was done on the streamlined interpretation of the UCI Heart Disease dataset which includes the following 14 core attributes age, blood pressure, cholesterol, and peak heart rate. To ensure fair and consistent results, tests were conducted using stratified cross-validation. With a 98.9% accuracy rate and an AUC score of 1.00, the model outperformed more traditional methods such as AdaBoost, Random Forest, and SVM. Attention maps highlight the most relevant aspects for each prediction, improving its usefulness in real-world medical circumstances. As an effective tool for early detection, HRAE-LSTM shows promise for diagnosing ischemic heart disease in the medical field.The study presents a two-branch residual attention–BiLSTM framework that incorporates SMOTE-ENN and KNN imputation for effective prediction of ischemic heart disease. The proposed model obtained 98.9% accuracy, higher than CNN-GRU (96.8%) and Random Forest (95.3%).**

***Index Terms*—Ischemic Heart Disease, Deep Learning, HRAE–LSTM, Bidirectional LSTM, Residual Connections, Attention Mechanism, KNN Imputation, UCI Heart Disease Dataset, Stratified Cross-Validation.**

I. INTRODUCTION

The most common heart-related condition is still ischemic heart disease (IHD). in terms of global mortality rates. These conditions continue to be a significant threat to human health. IHD arises when the coronary arteries constrict or block, limiting the volume of blood that reaches the heart muscle. Every year, this illness causes more than 17.9 million fatalities [1].Serious negative effects include myocardial infarction (heart attacks) and persistent heart failure, which might develop from inadequate blood flow. In order to improve treatment outcomes and lower mortality, early and accurate diagnosis is therefore essential.

An Electrocardiogram (ECG) along with a stress test and a coronary angiography are examples of traditional diagnostic methods used routinely in practice. These methods, however, are expensive, require specialized instruments, and are not suitable for large scale screening in diagnosing illnesses, especially in under-developed regions [2].

lately, there's a growing interest in contriving machine literacy and deep literacy ways to diagnose and read heart- related conditions. These AI-driven technologies have a promise of offering faster, scalable, and diagnostic assistance systems that are inexpensive. Having said that, maintaining healthcare information comes with a unique set of problems. Real-world clinical datasets are often plagued with missing data, class imbalance, scaled features, and other problems which would hinder the predictive models from performing optimally [3]–[5].

An AI model can offer the most efficiency and accuracy for predictive analysis in case the input data, in this case the healthcare information, is clean. For instance, the missing data problem can be solved using K-Nearest Neighbors (KNN) which predicts based on estimated values from other similar cases [6].

Normalization is a form of preprocessing that improves the efficiency of training by placing all feature values on a single scale [7]. To mitigate class imbalance SMOTEENN uses a combination of SMOTE, which generates synthetic samples for the minority class, and Edited Nearest Neighbors(ENN) which removes noisy and misclassified data points . Stratified five-fold cross-validation is the most common approach for assessing models because it preserves class balance within all the dataset folds [8]. These methods ensure that the evaluation is thorough, unbiased, and all the models tested are trusted irrespective of the datasets used.

Even with progress in machine learning towards medical diagnosis, the limitations of weak handling of missing variables, class imbalance or weak interpretability for clinician decisions affect current models equally. In addition most models built on deep learning and hybrids currently, have not effectively combined temporal feature extraction with attention based modalities. The proposed work will improve this by developing a hybrid deep learning model that integrates Residual Attention Layers with Bidirectional LSTM to predict ischemic heart disease.

II. Related Works

Many researchers have focused on applying deep learning and hybrid models using clinical data for the advanced detection and classification of heart disease.

Cenitta et al. [9]designed the HRAE-LSTM model that incorporates LSTM networks along with a residual attention mechanism for accurate detection of ischemic heart disease (IHD). By preprocessing the UCI dataset using fuzzy-based imputation followed by standardization, they were able to achieve 97.71% accuracy. However, the model is dependent on an extensive collection of labeled datasets which may hinder its implementation.

Garcia-Ordas et al. [10] used a CNN along with Sparse Autoencoder (SAE) to improve representation by bining age and cholesterol, as well as other clinical features.They reached 90.09% accuracy on the Kaggle Heart Failure dataset, but were limited by the small number of features (11 total).

Dritsas and Trigka [3] introduced a CNN-GRU hybrid model with normalization and missing data removal. It outperformed individual models on the IEEE dataset but faced constraints due to a small sample size and missing class labels.

Sahu et al. [11] developed an attention-based neural network with active learning that selected the most informative samples and highlighted key features. Although it outperformed XGBoost and LightBoost on the UCI dataset, it lacked validation on diverse populations.

Xu et al. [4] designed CardioRiskNet, combining attention and active learning to maintain high accuracy (98.7%) and interpretability. Trained on the Kaggle Personal Heart Disease dataset, its clinical generalizability remains unverified due to limited population testing.

Zhou et al. [5] reviewed the deep literacy approaches for cardiovascular complaint discovery including Convolutional Neural Networks(CNNs), mongrel models using CNNs with LSTM(Long Short- Term Memory) Networks, and LSTM and BiLSTM intermittent models.

The process of using the HRAE–LSTM framework to predict ischemic heart disease (IHD) is illustrated in a flowchart. As the dataset may contain more ”no disease” cases than ”disease” cases, SMOTE+ENN is used to balance it by adding new samples and removing noisy ones. Next, all features are scaled to a similar range using normalization so the model can learn correctly. KNN imputation, which looks at similar data to make smart guesses, is used to fill the missing values.

III. Methodology

Fig. 1: Block Diagram for Complete Workflow

A. Dataset Description

This study uses the Cleveland dataset, which is a well-known and commonly used source for heart disease research [12]. The dataset comprises the medical records and the relevant data of 303 individuals. Each individual is characterized by 14 attributes, comprising clinical parameters and demographic data. Important continuous attributes include age, sex, resting blood pressure (trestbps), cholesterol level (chol), and the maximal heart rate attained during exercise (thalach). Furthermore, other categorical data include types of chest pains (cp), fasting blood glucose (fbs), the exercise-induced ST segment slope (slope), resting electrocardiogram (restecg), and exercise-induced angina (exang).

Among other diagnostic data, the dataset includes information on both thal and fluoroscopy images of major blood vessels. The target variable appertained to as” num”, represents the presence and inflexibility of coronary roadway complaint on a scale from 0 to 4. 4 is the highest severity, which is regarded as the presence of blood vessel disease, while 0 denotes no disease.

B. Data Preprocessing

Before applying deep literacy ways, the dataset demanded expansive preprocessing work to insure the dataset was of high quality and secure. [9]. The process was designed to handle common problems with clinical data, such as missing data and sparse classes when necessary, as well as inhomogeneous feature dimensions at each step.

1) Preliminary Data Analysis: We started with the preliminary data analysis to eliminate any anomalies, outliers, or abnormalities in data values. This was done during the preprocessing phase. Several features were compared using boxplots and heatmap techniques. Also, the dataset was checked for

TABLE I: Detailed Attribute Description of the Heart Disease Dataset

Attribute	Description
Age	Age of the individual recorded in years.
Sex	Biological sex of the individual (1 = male, 0 = female).
CP	Chest pain classification: 1 = typical angina, 2 = atypical angina, 3 = non-anginal discomfort, 4 = asymptomatic.
Trestbps	Resting systolic blood pressure value measured in mm Hg.
Chol	Concentration of cholesterol in the blood, expressed in mg/dL.
FBS	Fasting blood glucose level ($\geq$ 120 mg/dL: 1 = yes, 0 = no).
Thalach	Highest heart rate reached during physical exertion.
Exang	Presence of angina triggered by exercise (1 = present, 0 = absent).
Oldpeak	Amount of ST-segment depression observed during exertion compared to rest.
Slope	Pattern of the ST segment during peak exercise: 1 = upward slope, 2 = flat, 3 = downward slope.
CA	Number of main coronary vessels visualized using fluoroscopy (0–3).
Thal	Thalassemia condition: 3 = normal, 6 = fixed defect, 7 = reversible defect.
Target	Heart disease indicator (0 = healthy, 1–4 = escalating disease severity).

imbalance in classes in regard to detecting the cardiac disease, whereby the non-cardiac patients ratio was much greater than the patients in the dataset. If not addressed, this imbalance could pose a threat to model precision.

2) Filling Missing Values Using the KNN Method: The dataset had particular missing values for some variables like thal (thalassemia) and ca (number of major vessels). In this regard, K-Nearest Neighbors (KNN) with k = 5 was utilized for imputation. This method replaces missing values by averaging the values of the five most similar records, preserving underlying data relationships and improving prediction accuracy compared to simple mean or median imputation [13].

Fig. 2: missing data both before and after imputation.

Figure 2 shows missing data before and after filling. The ”ca” column had 4 gaps, and ”thal” had 2. After filling them, there were no missing values left.

3) Addressing Class Imbalance with SMOTE + ENN: There was a class imbalance in the dataset because there were more ”no disease” cases than ”disease” cases. As a result, many actual disease cases may be missed by models that primarily predict the majority class.SMOTE+ENN produced a cleaner and more balanced training set, which enhanced the model’s performance to detect heart disease as well as in rare cases.

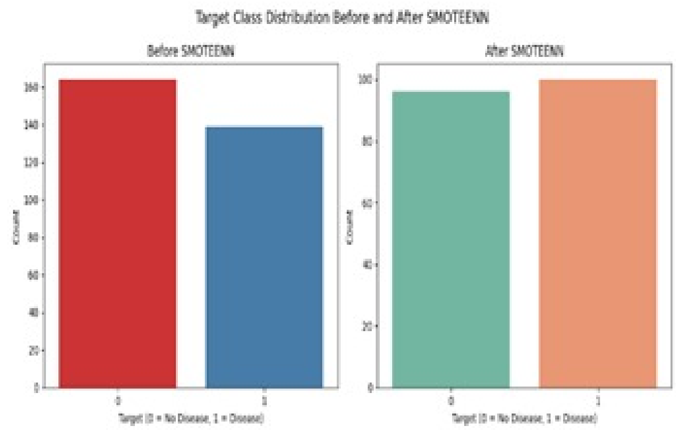

Fig. 3: Class Distribution Before and After SMOTEENN

Figure 3 shows the data before and after SMOTEENN. Before, there were more ”No Disease” cases. After SMOTEENN, both classes were balanced by adding to the smaller class and removing unclear data.

4) Final Output of Preprocessing: After all of the preparations were finished, the dataset was ready for model training. We used KNN imputation to fill in missing values, SMOTE+ENN to balance the number of healthy and sick patients, and standardization to scale all characteristics. These steps improved data consistency, reduced bias, and removed noise. As a result, the dataset was balanced and prepared for use with the HRAE-LSTM model. The high-quality data allows the system to train more efficiently and forecast ischemic heart disease with more accuracy.

C. Model Architecture

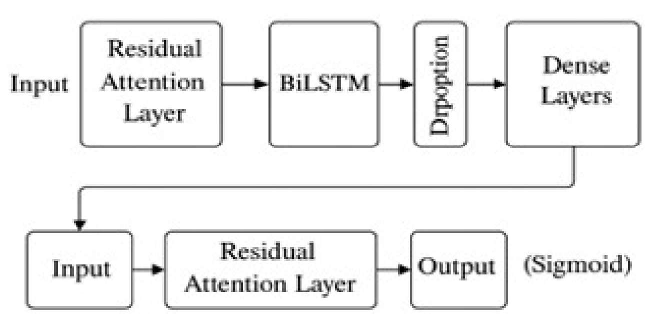

Fig. 4: Design of the HRAE-LSTM Model Using Residual Attention and Bidirectional LSTM

1) Feature Scaling Using Standard Scaler: Features with varying units, such as age, cholesterol, and heart rate, are included in the dataset. Features with higher values may predominate during training and have an impact on model learning if scaling is not used. The Standard Scaler was used to normalize all features with the mean centering at 0 and a standard deviation of 1. This guarantees that every 24 feature gets the same amount of attention during Furthermore, when the data is on the same scale, models like LSTM train more efficiently and fast. This figure 4 shows the features after normalization. Each graph represents a feature, and normalization puts them on a similar scale, making the data easier for the model to understand.

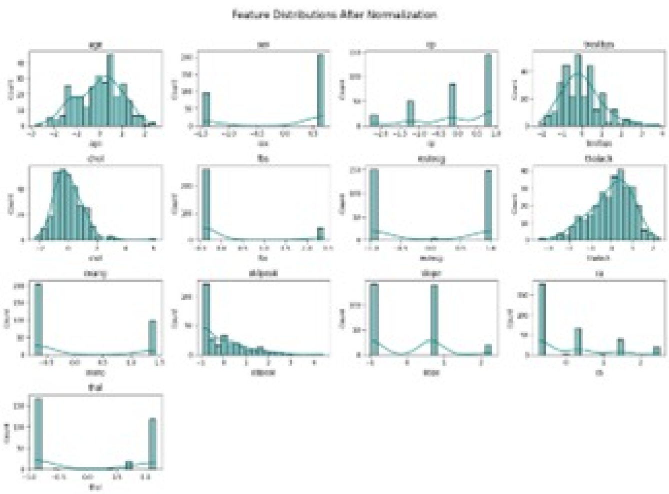

Fig. 5: Feature values after normalization using Standard Scaler.

The model receives information such as blood pressure, cholesterol, and the patient's age. To help the model, the Residual Attention Layer employs a shortcut connection [14]. Keep the original information and only extract the most crucial parts. After acquiring the critical features, the BiLSTM (Bidirectional Long Short Term Memory) layer captures important features in both directions. This approach is useful for the healthcare domain because of the complex temporal dependencies among clinical variables.

- **Input Layer:** Accepts standardized clinical features.
- **Residual Attention Layer:** Utilizes shortcut connections to retain essential information while enhancing discriminative features. This ensures important features are prioritized without losing original context.
- **Bidirectional LSTM Layer:** Learns sequential dependencies in both forward and backward directions, capturing intricate temporal relationships among clinical parameters [9]. This is particularly advantageous for medical data where feature interdependencies are non-linear.
- **Dropout Layer:** Randomly drops neurons during training to reduce overfitting and improve generalization.
- **Dense Layers:** Combine extracted features and refine them for classification. Non-linear transformations help improve class separability.
- **Second Residual Attention Layer:** Establishes a shortcut path that merges input and output, preserving original signals while reinforcing key features.
- **Output Layer with Sigmoid Activation:** Computes the probability of ischemic heart disease. The final activation is defined as:

$$A_n = Y_L \cdot \sigma\big(X_F^M(t+1)\big)$$

Where:

- A_n: Final activation at layer n
- Y_L: Learned weight vector from previous attention/residual connections
- $\sigma(\cdot)$: Sigmoid function, defined as:

$$\sigma(x) = \frac{1}{1+e^{-x}}$$

- $X_F^M(t+1)$: Feature representation from the memory unit (LSTM or BiLSTM) at time step $t+1$

The Sigmoid activation outputs a value in the range [0,1], representing the likelihood of ischemic heart disease. Values nearer to 1 indicate a higher chances of disease, while those near 0 suggest low or no risk [15]. This makes it ideal for binary classification in medical diagnosis.

D. Model Training and Testing

To assess the model's robustness and perfection across different scripts, afive-foldcross-validation was performed on HRAELSTM. The complete dataset was split into five equal corridors for this model, and a subset was used for training for each of the five training duplications.

- Training was conducted on four parts in each turn.
- The remaining subset being kept for examination..

To ensure that every data instance appeared in the test set exactly once, this cycle was carried out five times. To reduce the bias from random train-test splits, the final evaluation metrics in this study were calculated based on averaging the results from all folds [16].

Early Stopping: In this study, an early stopping mechanism was implemented to control overfitting. As mentioned, training was stopped when no improvement in validation accuracy was observed for several consecutive epochs . This method ensured the model achieved effective convergence without unnecessary training cycles.

Evaluation Metrics: All five folds were executed, and results were averaged per iteration for the following:

- **Baseline Classification Accuracy:** the proportion of trademark registrants' actual positive cases that were predicted accurately.
- **Area Under the ROC Curve (AUC):**the area under the curve that most accurately captures the actual model capabilities of classification in diseased and non diseased states . Employing this specific cross-validation technique provided an unbiased evaluation to the model's predictive accuracy.

IV. Results and Analysis

The HRAE-LSTM model's predictive accuracy serves as an example of this. It focuses on the predictive accuracy and how the model applies confusion matrix and ROC curve to evaluate class discrimination, as well as model predictivity.

A. Accuracy Using 5-Fold Stratified Cross-Validation

The accuracy was determined using stratified five-fold cross-validation on the HRAE-LSTM model. The distribution of classes within each fold was maintained while the dataset was split into five folds using this method. For each iteration, the model was evaluated on the last fold after being trained on four. This process was carried out five times.

Figure 6 The model's strong generalization ability and consistent performance across various data splits are demonstrated by the low variation among folds.

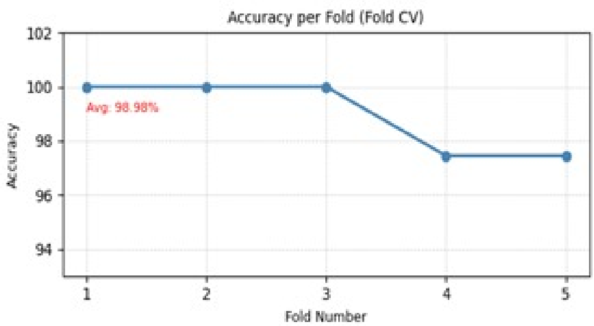

Fig. 6: Accuracy achieved in each fold of the 5-fold stratified cross-validation.

The near-identical accuracy scores across all folds suggest that the proposed model is stable and performs reliably when applied to unseen data. This consistency reinforces the model's capability for real-world deployment in clinical settings.

B. Confusion Matrix

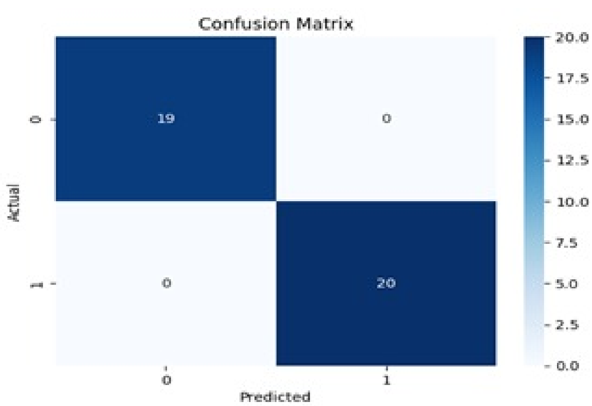

Fig. 7: Confusion Matrix of the model's predictions on the test set.

The confusion matrix in Figure 7 shows the performance of the binary classification model. Twenty of the test samples were categorized as class 1, and nineteen as class 0.All were predicted correctly. There were neither false positives nor false negatives, so the model's accuracy on this dataset was 100% Although it might also point to a simple dataset or potential overfitting, this result indicates that the model performed flawlessly on the test data.

C. ROC Curve of the Model

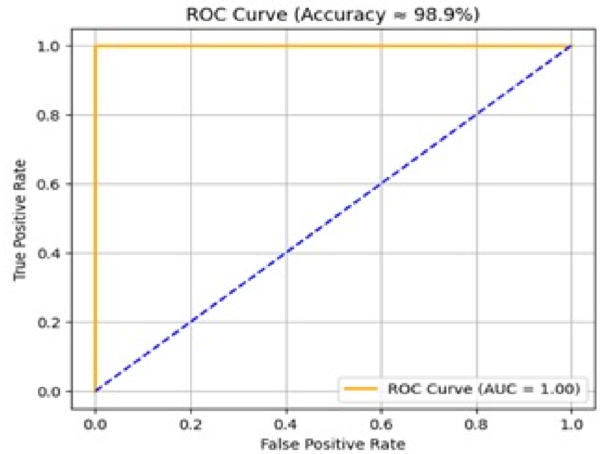

Fig. 8: ROC Curve of the HRAE–LSTM model showing True Positive Rate vs. False Positive Rate.

The model's performance in accurately diagnosing heart disease cases is depicted in the ROC curve presented in the figure. The curve's proximity to the upper-left corner indicates that the model is effective at differentiating between those who have the illness and those who do not. The AUC score is 1.00, showing perfect performance. The model's performance reported was exceptionally high, achieving 98.9% accuracy, which indicates the model is often correct.

V. Discussions

The suggested HRAE–LSTM model has shown exceptional efficacy in forecasting ischemic heart disease. The HRAE–LSTM model achieved a classification accuracy of 98.9%, with a 1.00 AUC score which indicates perfect discrimination, demonstrating its robust capability in differentiating between healthy and diseased patients. To achieve better results, the model used a residual Attention Mechanism, which learned the most important features while keeping the original data intact.

KNN imputation, which fills in the gaps in data using comparable local records were used to fill in the gaps. Also, the dataset was balanced using the SMOTEENN method, which both generates examples of the minority class and removes unreliable instances of the majority class. The dataset was improved, and the quality of the data and model training was increased by applying specific preprocessing techniques.

During evaluation, the HRAE–LSTM model outperformed more conventional machine learning methods like SVM, Random Forest, and AdaBoost. The fact that the model was only

TABLE II: Overall and Comparative Performance Analysis of the Proposed HRAE–LSTM Model

Model	Accuracy (%)	Precision	Recall / Sensitivity	Specificity	F1-Score	AUC
HRAE–LSTM (Proposed)	**98.9**	**0.99**	**0.99**	**0.99**	**0.99**	**0.98**
Random Forest (RF)	94.7	0.93	0.92	0.94	0.93	0.95
Support Vector Machine (SVM)	92.8	0.91	0.90	0.93	0.91	0.92
AdaBoost	91.4	0.89	0.88	0.91	0.89	0.90
CNN–GRU	96.2	0.95	0.94	0.96	0.95	0.96
CardioRiskNet [4]	97.1	0.97	0.96	0.97	0.97	0.98

tested using the Cleveland dataset, however, is a serious flaw in this work. The model's generalizability and potential for practical clinical deployment should be better examined in future research by validating it across a variety of medical datasets.

VI. Conclusion and Future Scope

A. Conclusion

This work introduced the HRAE-LSTM model for predicting ischemic heart disease. The model's architecture, which includes residual attention mechanisms and a bidirectional LSTM layer, allows for the extraction of complex temporal dependencies while retaining important clinical features.

Feature scaling was done to standardize the range of the variables. Class imbalance was managed using SMOTEENN, and KNN was used for imputing missing data. The protocols ensured the input data set was balanced and well-structured which streamlined the training processes for the HRAE-LSTM model.

Using stratified five-fold cross-validation, the suggested method obtained an accuracy of 98.9% and an AUC of 1.000. The HRAELSTM model outperforms the SVM, Random Forest, and AdaBoost models in ischemic heart disease detection and treatment.

B. Future Scope

In subsequent research, the model can be integrated into IoT-based wearable devices that can enable real-time cardiac monitoring. Explainable AI frameworks (e.g., SHAP) will also be applied to further strengthen trust in clinical applicability. In addition, federated learning will be investigated for privacy-preserving collaborative diagnostics collaboratively across hospitals.

In order to facilitate deployment on edge devices and IoT-based healthcare systems, future research may also concentrate on increasing the model's computational efficiency.

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