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Heart Attack Risk Assessment Using Deep Learning with Feature Optimization

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Abstract- Heart attacks remain a critical global health issue, necessitating accurate predictive models to identify at- risk individuals and support preventive care. This project, titled "Heart Attack Risk Assessment Using Deep Learning with Feature Optimization," applies deep learning techniques to assess the likelihood of a heart attack. The study utilizes a Fully Connected Neural Network (FCNN) model enhanced by feature optimization methods, ensuring that the most relevant predictors are prioritized. Additionally, the project incorporates risk visualization, enabling clear and actionable insights for early detection and management of heart attack risks.

Index Terms- Deep Learning, Feature Optimization, Heart Attack Risk, Visualization.

I. INTRODUCTION

Heart attacks, a leading cause of morbidity and mortality worldwide, demand early and accurate prediction to mitigate associated risks. With advancements in artificial intelligence and machine learning, healthcare has witnessed a paradigm shift towards data-driven approaches for disease prediction and management. These techniques have shown promise in identifying risk patterns, enabling proactive measures and personalized healthcare interventions. This paper focuses on the application of deep learning techniques for heart attack risk assessment. Traditional methods often rely on basic statistical analysis, which may fail to capture complex, non-linear relationships within clinical data. In contrast, deep learning models, particularly Fully Connected Neural Networks (FCNNs), offer the capability to handle large, multidimensional datasets and extract meaningful patterns for predictive analytics.

II. LITERATURE SURVEY

[1] Mahlknecht et al. (2023) explored the application of machine learning for cardiovascular disease prediction, specifically focusing on heart attack risk. The study examined various deep learning models and their performance in classifying heart attack risks. The authors identified that feature engineering and preprocessing techniques, such as normalization and imbalanced dataset handling, are crucial to improving the predictive accuracy of deep learning models in medical applications. Their findings emphasize the importance of robust data preprocessing strategies for effective heart attack risk prediction.

[2] Amin et al. (2021) proposed an ensemble learning approach for heart disease prediction using clinical datasets. Their study integrated multiple machine learning models, including decision trees and support vector machines, to improve classification accuracy. They highlighted the effectiveness of ensemble methods in handling noisy data and achieving higher reliability in real-world medical applications.

[3] Smith et al. (2022) investigated the application of hybrid feature selection methods for enhancing deep learning-based heart disease prediction systems. The research combined filter and wrapper techniques to identify the most significant features, resulting in a model with reduced complexity and improved accuracy. The study underscores the importance of effective feature selection for optimizing model performance in healthcare.

[4] Johnson et al. (2024) introduced a predictive model that integrates deep learning with feature optimization techniques for cardiovascular disease diagnosis. Their work focused on addressing data imbalance and improving generalization by using advanced optimization algorithms. The results demonstrated the potential of deep learning models to outperform traditional machine learning methods in predicting heart-related conditions.

Objectives

- Develop a Predictive Model: Create a deep learning-based system using Fully Connected Neural Networks (FCNNs) to accurately assess heart attack risk by analyzing multidimensional clinical data.
- Implement Feature Optimization: Employ feature optimization techniques to identify and utilize the most relevant predictors, ensuring the model is both efficient and interpretable.

- Evaluate Model Performance Thoroughly: Assess the system using comprehensive metrics like accuracy, precision, recall, and F1-score to ensure robust and unbiased predictions.
- Enable Risk Visualization: Provide intuitive and actionable visual representations of the heart attack risk, empowering medical professionals and individuals to make informed decisions.
- Promote Early Intervention: Facilitate the early detection of high-risk individuals, enabling timely preventive measures and personalized healthcare strategies.

III. METHODOLOGY

This project employs a deep learning approach to assess heart attack risk using a Fully Connected Neural Network (FCNN). The methodology includes the following steps:

Data Preprocessing
The dataset is preprocessed to ensure compatibility with the deep learning model. Categorical variables are transformed into numerical formats using label encoding, while numerical variables are standardized to normalize their ranges. These preprocessing steps help ensure that the model can process all features effectively and that no single feature dominates the learning process.

Feature Optimization
To improve the model's accuracy and efficiency, feature optimization is performed using the SelectKBest method with mutual_info_classif, which selects the most relevant features based on their mutual information with the target variable (heart attack risk). This process helps reduce dimensionality by eliminating irrelevant or redundant features, allowing the model to focus on the most impactful predictors. This step enhances both the performance and interpretability of the model by ensuring that only the most significant features are included in the final model.

Model Development
The core of the methodology is the development of the deep learning model using a Fully Connected Neural Network (FCNN). The model architecture includes an input layer, two hidden layers with ReLU (Rectified Linear Unit) activation, and dropout layers to reduce overfitting. The output layer uses sigmoid activation to produce a binary classification output (heart attack risk: high or low). The model is compiled using the Adam optimizer, which adapts the learning rate during training, and binary cross-entropy loss, which is appropriate for binary classification tasks. This setup ensures that the model learns to distinguish between high-risk and low- risk heart attack cases effectively.

Training and Evaluation
The model is trained using the training dataset, with an early stopping mechanism that halts training if the validation loss does not improve after a specified number of epochs, thus preventing overfitting. After training, the model is evaluated using various metrics, such as accuracy, precision, recall, and F1-score, to assess its performance in classifying heart attack risk. These metrics provide a well-rounded view of the model's ability to make accurate and reliable predictions.

IV. PROPOSED SYSTEM

The proposed system is designed to assess the risk of heart attacks using a deep learning model that leverages optimized features for accurate predictions. The system is structured to provide users with an intuitive interface and actionable insights based on the prediction results.

1. Data Input and Preprocessing
The system accepts user-provided inputs through an interface, where health and medical parameters relevant to heart attack risk are entered. These inputs undergo preprocessing to ensure compatibility with the deep learning model. Categorical variables are transformed into numerical formats using label encoding, while numerical variables are standardized to normalize their scales. These steps ensure the model can handle diverse inputs effectively and maintain consistent performance.

2. Feature Optimization
To enhance the system's accuracy and efficiency, feature optimization is performed using mutual information- based feature selection. This method identifies the most relevant predictors of heart attack risk by evaluating their relationship with the target variable. By eliminating redundant or less significant features, the system reduces noise, improves performance, and focuses on the most impactful data.

3. Deep Learning Model
The heart of the system is a Fully Connected Neural Network (FCNN) designed specifically for binary classification. The model comprises:

- Input layer to process the optimized feature set.
- Hidden layers with ReLU activation functions and dropout to improve generalization and prevent overfitting.
- An output layer with a sigmoid activation function to classify heart attack risk as either high or low.

The model is trained to achieve high accuracy and reliability, ensuring robust performance on real- world inputs.

Risk Prediction and Visualization

Based on the processed input data, the system predicts the likelihood of a heart attack. The prediction result is presented to the user in an easily understandable format, including a clear visualization of the risk level. This visualization helps users interpret the results quickly and effectively.

Lifestyle-Based Suggestions

In addition to risk prediction, the system offers personalized lifestyle recommendations based on the user's risk level. These suggestions are designed to help users make informed decisions and adopt healthier habits to mitigate their risk of a heart attack.

Model Architecture

- Input Layer: The number of input units equals the number of features selected from the dataset.
- Hidden Layers:
- First Hidden Layer: Units = n1, Activation= ReLU
- Second Hidden Layer: Units = n2, Activation = ReLU
- Dropout: Applied to reduce overfitting.

- Output Layer:
- Units = 1 (for binary classification: Heart Attack: Yes/No)
- Activation = Sigmoid (to output a probability score between 0 and 1).

Model Compilation

- Optimizer: Adam optimizer (adaptive learning rate)
- Loss Function: Binary Cross-Entropy (since it is a binary classification task)

$$Binary\ Cross-Entropy\ Loss = -[y \cdot log(p) + (1-y) \cdot log(1-p)]$$

Where:
- y: True label (0 or 1).
- p: Predicted probability (output of the sigmoid function, $\sigma(x)$).
- Evaluation Metric: Accuracy (since we are working with binary classification)

Model Training

- Train the FCNN using the training data. The model updates its weights based on the loss function using backpropagation and the Adam optimizer.

Activation Functions

- ReLU Activation for Hidden Layers:

$$ReLU(x) = \max(0, x)$$

Output is x if x>; otherwise, it outputs 0

- ReLU activation is used in the hidden layers to introduce non-linearity, helping the model learn complex patterns.
- Sigmoid Activation for Output Layer:

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

The sigmoid function maps the input x to the range [0,1]

- Sigmoid function is used in the output layer to map the output to a probability between 0 and 1, indicating the likelihood of a heart attack.

Final Output

- The model outputs a probability score between 0 and 1. If the score is greater than a threshold, the result is classified as "Heart Attack: Yes"; otherwise, it's classified as "Heart Attack: No".

The interface, as shown in the figure, represents the interactive module of the Heart Attack Risk Assessment System. This application allows users to input key health parameters, including demographic details, clinical measurements, and lifestyle-related factors. Upon submission, the system predicts the risk of a heart attack, categorizing it into Low Risk or High Risk.

The circular visualization displays the predicted risk level, providing a clear and concise representation for users. Additionally, the interface generates personalized lifestyle suggestions, such as dietary changes or exercise routines, tailored to the individual's assessed risk. This user-friendly design bridges the gap between complex predictive analytics and practical healthcare applications, ensuring accessibility for both healthcare providers and patients.

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Classification Report:
              precision    recall  f1-score   support

           0       0.82      0.88      0.85        77
           1       0.91      0.86      0.88       107

    accuracy                           0.87       184
   macro avg       0.87      0.87      0.87       184
weighted avg       0.87      0.87      0.87       184

Confusion Matrix:
[[68  9]
 [15 92]]
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The classification report and confusion matrix summarize the performance of the proposed model in assessing heart attack risk. The model achieved an accuracy of 87%, demonstrating balanced performance across both classes. Precision, recall, and F1-score values for "Heart Attack: No" (Class 0) are 0.82, 0.88, and 0.85, respectively, while for "Heart Attack: Yes" (Class 1), they are 0.91, 0.86, and 0.88, respectively. The confusion matrix highlights that the model correctly classified 68 instances of "No" and 92 instances of "Yes," with 9 and 15 misclassifications, respectively. The macro and weighted averages of precision, recall, and F1-score further validate the model's ability to handle both classes effectively, emphasizing the reliability of the feature- optimized deep learning approach used in this study.

V. CONCLUSION

In conclusion, Heart attack risk assessment through deep learning has emerged as a transformative approach in modern healthcare. Fully Connected Neural Networks (FCNNs) provide the computational capability to analyze intricate patterns in medical data, delivering more precise and actionable insights than conventional methods. Employing feature optimization ensures that only the most influential factors contribute to the model's predictions, enhancing both performance and interpretability. Risk visualization complements this analytical framework by presenting the outcomes in an intuitive manner, enabling individuals and clinicians to understand and act upon the insights effectively. This integration bridges the gap between advanced computational methods and practical healthcare applications, emphasizing the role of technology in improving patient outcomes.

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