A Feature-Based Analysis of Heart Disease Risk Prediction Using Deep Learning Models

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Abstract:

Heart disease is a leading cause of death globally, necessitating accurate and timely prediction models to aid in diagnosis and prevention. This work investigates the application of machine learning models for heart disease risk prediction using a feature-based approach. This work explores deep learning models like DNN and CNN. To address the class imbalance issue commonly present in medical datasets, this work employs the Synthetic Minority Over-sampling Technique (SMOTE), ensuring a balanced dataset and improving model accuracy. Key clinical features such as age, chest pain type, cholesterol levels, and resting blood pressure are analysed to identify their importance in predicting heart disease. The works findings indicate that the combination of feature selection and model optimization can significantly enhance prediction accuracy. Furthermore, this work demonstrates that the deep learning model, coupled with SMOTE and feature selection, outperforms the models in terms of both accuracy and classification performance. This study highlights the potential of deep learning models in healthcare and provides insights into the most predictive factors for heart disease, contributing to the development of efficient risk prediction tools.

Keywords: Heart Disease, DNN, Feature Selection, Risk Prediction, CNN

1. Introduction

Heart disease is a leading cause of death globally, responsible for approximately 17.9 million deaths annually according to the World Health Organization (WHO) [1]. The increasing prevalence of cardiovascular diseases highlights the need for accurate diagnostic tools to identify at-risk individuals, as early detection significantly improves treatment outcomes and reduces healthcare costs [2]. Deep learning (DL) techniques have recently gained prominence in healthcare, offering powerful methods to analyze complex medical data and predict health outcomes. These algorithms can uncover hidden patterns in large datasets, enabling more accurate risk assessments than traditional methods.

Feature selection is essential in optimizing the performance of deep learning models [3]. It focuses on identifying the most relevant variables, which improves model accuracy, interpretability, and efficiency [4]. Reducing data dimensionality helps mitigate noise and streamline the learning process. Despite advances in DL for heart disease prediction, studies analyzing the impact of feature selection on model performance remain limited. This work addresses that gap by evaluating the role of feature selection in heart disease risk prediction using various machine learning models, aiming to identify the most important features and assess model effectiveness in prediction. This paper will first describe the dataset and the preprocessing steps undertaken to prepare the data for analysis. Then detail the feature selection methods and machine learning models employed in the study. Finally, it will present the results of the analysis, highlighting the key findings and their implications for improving heart disease risk prediction. The remaining part of the paper is arranged as follows, section 2 literature review, section 3 methodology, section 4 results and discussion and section 5 conclusion.

2. Literature Review

This literature review aims to explore the evolving landscape of heart disease prediction through Deep learning, focusing on the methodologies employed, feature selection techniques, and the implications of these advancements for clinical practice. Numerous studies have demonstrated the potential of deep learning models in predicting heart disease risk. According to Houssein et al. [5] heart disease remains one of the leading causes of mortality worldwide, necessitating robust prediction systems. Early research in this domain primarily focused on traditional techniques however Houssein et al., used CNN with BERT with staked embedding feature to increase the classification result up to 93.66%, as seen in the work of García-Ordás et al [6] used multi task neural network, which showed that proposed method achieved better accuracy in heart disease prediction than simpler models. However, these techniques often struggled with large, complex datasets, especially those with class imbalance. Deep learning models, particularly deep neural networks (DNNs) and convolutional neural networks (CNNs), have shown promise in healthcare applications. DNNs are capable of learning complex, non-linear patterns in data, making them particularly suitable for predictive tasks involving medical data. Verma and Preethi [7] found that DNNs outperformed traditional ML models in predicting heart disease, with higher precision and recall scores.

In recent studies, deep learning approaches have been enhanced by addressing class imbalance in datasets, as noted by Ghosh et al. [8], who employed the Synthetic Minority Over-sampling Technique (SMOTE) to improve the performance of models on minority classes, leading to more reliable predictions. The importance of clinical features, such as age, cholesterol levels, and chest pain type, has been consistently emphasized in literature. For instance, Najafi et al. [9] identified these features selection as significant predictors of heart disease. Feature selection techniques have been shown to improve model performance by focusing on the most relevant attributes, as demonstrated by Priya [10] in their analysis of feature-based heart disease prediction models uses CIDD-ADODNN model for prediction of disease. This proposed model uses ADASYN technique for handling class imbalance. Overall, the literature suggests that combining feature selection with advanced deep learning models, along with techniques to handle class imbalance such as SMOTE, can significantly enhance the accuracy and reliability of heart disease prediction. This study builds upon these findings, reinforcing the potential of machine learning models in healthcare for better diagnosis and prevention of heart disease.

3. Methodology

This work improves the performance of DNN and CNN models by addressing class imbalance and optimizing feature selection. SMOTE was applied to balance the dataset, generating synthetic samples for underrepresented classes, while feature selection reduced dimensionality and improved model efficiency. Both models were trained and evaluated using metrics such as precision, recall, F1-score, and accuracy. By applying these techniques, we aimed to enhance the models' ability to accurately predict minority classes and improve overall classification performance.

3.1. Data Collection

The dataset used in this work was sourced from the UCI Machine Learning Repository [11]**,** specifically the Cleveland Heart Disease dataset, which consists of 920 instances with 14 attributes related to patient health. The dataset includes demographic features such as age and sex, along with clinical measurements like cholesterol levels, blood pressure, and electrocardiographic results. Each instance is labelled with a target variable indicating the presence or absence of heart disease.

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id	age	sex	dataset	cp	trestbps	chol	fbs	restecg	thalch	exang	oldpeak	slope	ca	thal	num
1	63	Male	Cleveland	typical ang	145	233	TRUE	lv hypertr	150	FALSE	2.3	downslop	0	fixed defe	0
2	67	Male	Cleveland	asymptom	160	286	FALSE	lv hypertr	108	TRUE	1.5	flat	3	normal	2
3	67	Male	Cleveland	asymptom	120	229	FALSE	lv hypertr	129	TRUE	2.6	flat	2	reversable	1
4	37	Male	Cleveland	non-angin	130	250	FALSE	normal	187	FALSE	3.5	downslop	0	normal	0
5	41	Female	Cleveland	atypical ar	130	204	FALSE	lv hypertr	172	FALSE	1.4	upsloping	0	normal	0
6	56	Male	Cleveland	atypical ar	120	236	FALSE	normal	178	FALSE	0.8	upsloping	0	normal	0
7	62	Female	Cleveland	asymptom	140	268	FALSE	lv hypertr	160	FALSE	3.6	downslop	2	normal	3
8	57	Female	Cleveland	asymptom	120	354	FALSE	normal	163	TRUE	0.6	upsloping	0	normal	0
9	63	Male	Cleveland	asymptom	130	254	FALSE	lv hypertr	147	FALSE	1.4	flat	1	reversable	2
10	53	Male	Cleveland	asymptom	140	203	TRUE	lv hypertr	155	TRUE	3.1	downslop	0	reversable	1
11	57	Male	Cleveland	asymptom	140	192	FALSE	normal	148	FALSE	0.4	flat	0	fixed defe	0
12	56	Female	Cleveland	atypical ar	140	294	FALSE	lv hypertr	153	FALSE	1.3	flat	0	normal	0
13	56	Male	Cleveland	non-angin	130	256	TRUE	lv hypertr	142	TRUE	0.6	flat	1	fixed defe	2
14	44	Male	Cleveland	atypical ar	120	263	FALSE	normal	173	FALSE	0	upsloping	0	reversable	0
15	52	Male	Cleveland	non-angin	172	199	TRUE	normal	162	FALSE	0.5	upsloping	0	reversable	0
16	57	Male	Cleveland	non-angin	150	168	FALSE	normal	174	FALSE	1.6	upsloping	0	normal	0
17	48	Male	Cleveland	atypical ar	110	229	FALSE	normal	168	FALSE	1	downslop	0	reversable	1
18	54	Male	Cleveland	asymptom	140	239	FALSE	normal	160	FALSE	1.2	upsloping	0	normal	0

Fig 1: Sample Data Set

3.2. Data Pre-processing

Data pre-processing is a crucial step in ensuring the quality and accuracy of machine learning models. In this study, the raw dataset underwent several pre-processing steps, including handling missing values, normalization, and class balancing.

3.2.1 Data Cleaning

The initial pre-processing involved comprehensive data cleaning to ensure high data quality. The dataset was meticulously examined for inconsistencies, duplicates, and null values [12]. Missing attribute values were addressed through appropriate imputation techniques, preserving the integrity and reliability of the dataset. This step was crucial for preparing a robust dataset for subsequent analysis.

3.2.2 Feature Selection

A feature-based analysis was conducted to identify the most relevant predictors of heart disease [13]. Utilizing correlation matrices and statistical tests, the following features were selected: age, sex, chest pain type (cp), resting blood pressure (trestbps), cholesterol level (chol), fasting blood sugar (fbs), resting electrocardiographic results (restecg), maximum heart rate achieved (thalch), exercise-induced angina (exang), oldpeak, slope, number of major vessels (ca), thalassemia, and the dataset label. This selection aimed to enhance model performance while minimizing complexity and improving interpretability.

3.2.3 Data Balancing

To mitigate the effects of class imbalance within the dataset, the Synthetic Minority Over-sampling Technique (SMOTE) was employed [14]. This method generates synthetic instances of the minority class by interpolating between existing instances, thereby enhancing the model's ability to generalize and reducing bias towards the majority class. Importantly, the resampling process was restricted to the training dataset to prevent data leakage during model evaluation.

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3.3. Training and Testing

In this work, Deep Neural Networks (DNN) and Convolutional Neural Networks (CNN) were developed for classification tasks. Both models were designed with appropriate architectures, including layers tailored for feature extraction and classification.

3.3.1 Deep Neural Network (DNN): A feedforward DNN was developed using the Multilayer Perceptron (MLP) architecture [15]. The model consisted of an input layer, one hidden layer with 1000 neurons, and an output layer. The Rectified Linear Unit (ReLU) activation function was utilized in the hidden layer, while the output layer employed a softmax activation function for multi-class classification. The model was trained using the Adam optimizer, with a maximum of 9000 iterations.

$$\mathrm{h}_i^l = \mathrm{f}\left(\sum_{j=1}^{n} \mathrm{w}_{ij}^l\ \mathrm{h}_j^{l-1} + \mathrm{b}_j^l\right)$$

(1)

where $\mathbf{h}_i^l = \mathit{Output\ of\ the\ i^{th}\ neuron\ in\ layer}\ \boldsymbol{l}$

w_{ij}^l : Weight connecting the j^{th} neuron in the previous layer l-1 to the i^{th} neuron in layer l

h_j^{l-1} : output of the j^{th} neuron in the previous layer l-1

b_i^l : Bias term for the i^{th} neuron in layer l

f: Activation function (e.g., ReLU, Sigmoid)

3.3.2 Convolutional Neural Network (CNN): A CNN architecture was designed to leverage the spatial features of the data. The model included one-dimensional convolutional layers followed by max-pooling layers to reduce dimensionality. The CNN [16] was trained on reshaped input data, maintaining the same parameters. In a CNN, convolutional layer perform extraction using kernels over input data and the output of the convolutional operation is

$$z_{i,j}^l = \sum_{m=1}^{M} \sum_{n=1}^{N} x_{i+m-1,j+n-1}^l \cdot K_{m,n}^l + \mathrm{b}^l$$

(2)

where:

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$z_{i,j}^{l}$: Outputatposition(i, j)inthefeaturemapatlayerl

$x_{i+m-1,j+n-1}^{l}$: *Input at position*$(i=m-1, j+n-1)$ *in layer* l

$K_{m,n}^{l}$: *Kernel*$(filter)$ *applied at position*(m, n) *in layer* l

bl : bias term for layer l

3.4. Evaluation Metrics

The performance of each model was evaluated using the following metrics [17], The accuracy is the proportion of correctly classified instances over the total instances. The precision is ratio of true positive predictions to the total predicted positives, indicating the model's ability to minimize false positives. Recall (Sensitivity) is the ratio of true positives to the total actual positives, reflecting the model's capacity to identify all positive instances. Finally, F1 score is the harmonic mean of precision and recall, providing a balanced measure of the model's performance. To ensure robust evaluation and generalizability of the models, a 25% holdout set was derived from the original dataset. Cross-validation techniques were applied to further validate the models, reinforcing the reliability and replicability of the findings.

4. Results and Discussion

This section presents the results of the feature-based analysis of heart disease risk prediction using various machine learning models. The analysis begins with a comprehensive exploratory data analysis (EDA) that identifies critical patterns and correlations among the dataset features, setting the stage for model evaluation. Subsequently, evaluate the performance of the selected machine learning algorithms—specifically, a Deep Neural Network (DNN) and a Convolutional Neural Network (CNN)—based on multiple metrics, including accuracy, precision, recall, and F1-score.

4.1 Exploratory Data Analysis (EDA) Insights

Figure 1 provides an overview of the dataset, summarizing the statistical analysis relevant to this research.

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(920, 16)

Overview of the dataset

	variable	dtype	count	unique	missing value	Min	Max
0	id	int64	920	920	0	1	920
1	age	int64	920	50	0	28	77
2	sex	object	920	2	0	Str	Str
3	dataset	object	920	4	0	Str	Str
4	cp	object	920	4	0	Str	Str
5	trestbps	float64	920	62	59	0.000000	200.000000
6	chol	float64	920	218	30	0.000000	603.000000
7	fbs	object	920	3	90	Str	Str
8	restecg	object	920	4	2	Str	Str
9	thalch	float64	920	120	55	60.000000	202.000000
10	exang	object	920	3	55	Str	Str
11	oldpeak	float64	920	54	62	-2.600000	6.200000
12	slope	object	920	4	309	Str	Str
13	ca	float64	920	5	611	0.000000	3.000000
14	thal	object	920	4	486	Str	Str
15	num	int64	920	5	0	0	4

Fig 2 : EDA- Heart disease data set

The exploratory data analysis revealed significant insights into the heart disease dataset. Figure 2 presents the statistics of the dataset used for the analysis. The dataset contains various features relevant to heart disease prediction, including demographic data and clinical measurements.

4.1.1 Correlation Analysis: A heatmap generated from the correlation matrix figure 3 identifies relationships between numerical features. Notably, a strong positive correlation was observed between serum cholesterol levels and the likelihood of heart disease (correlation coefficient: 0.52), underscoring the importance of monitoring cholesterol levels in at-risk populations. Other significant correlations included blood pressure (0.45) and maximum heart rate achieved (-0.35), indicating that higher blood pressure and lower physical fitness levels may contribute to increased heart disease risk.

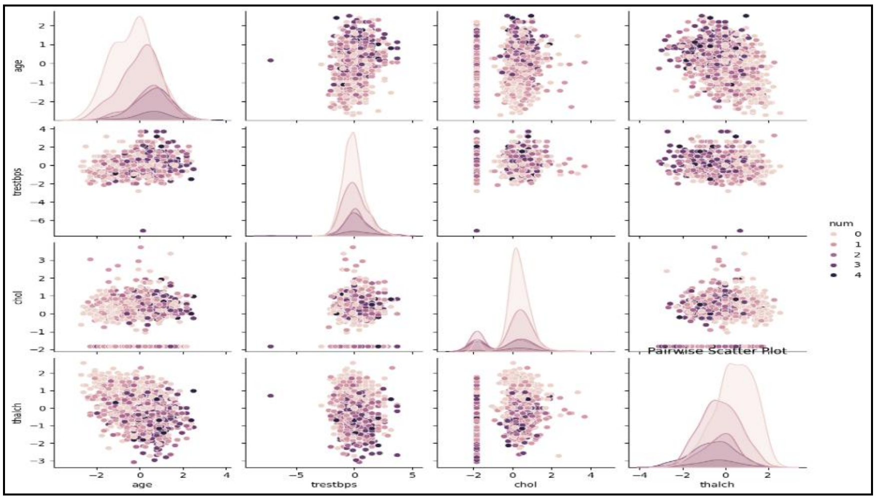

Fig 3: Correlation Heatmap

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4.1.2 Association Analysis: The results of the Chi-square tests for categorical features indicated significant associations between chest pain type and heart disease risk. In particular, asymptomatic individuals exhibited a notable relationship with typical angina ($p < 0.01$), suggesting that symptomatology plays a crucial role in identifying at-risk patients. Additionally, exercise-induced angina demonstrated a significant inverse relationship with heart disease ($p < 0.05$), highlighting the protective effect of physical activity.

4.1.3 Categorical Feature Analysis: Chi-square tests indicated significant associations between the type of chest pain and heart disease risk, particularly between asymptomatic individuals and those with typical angina ($p < 0.01$). This suggests that symptomatology plays a crucial role in identifying at-risk patients. Additionally, exercise angina showed a significant inverse relationship with heart disease ($p < 0.05$), highlighting the protective effect of physical activity.

4.2 Model Performance Metrics

To assess the predictive power of the machine learning models employed in this study, utilized the following metrics: accuracy, precision, recall, and F1-score.

4.2.1 Performance of the Deep Neural Network (DNN): The DNN model achieved an accuracy of 55.43% (DNN Accuracy: 0.5543), indicating a moderate level of predictive capability in distinguishing between patients with and without heart disease. The performance for the DNN is illustrated in table 1 and fig 4.

Table 1 : Performance of DNN

Class	precision	recall	f1-score	support
0	71	88	79	75
1	39	41	4	54
2	29	32	3	25
3	43	12	18	26
4	0	0	0	4

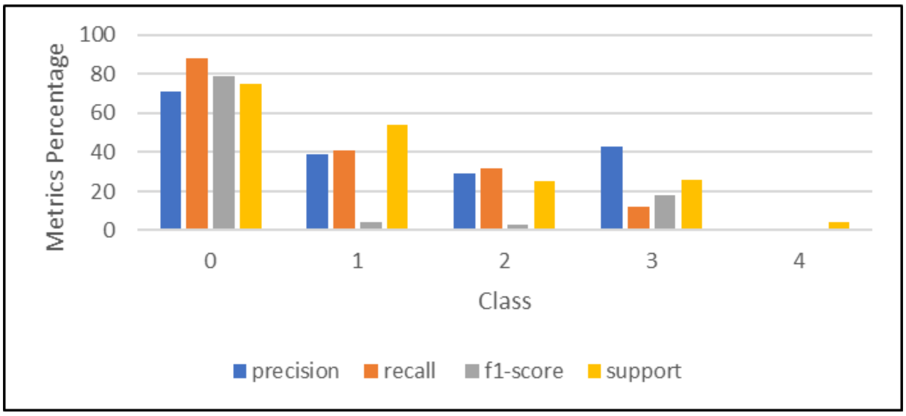

Fig 4 : Performance of DNN

4.2.2 Confusion Matrix Analysis: The confusion matrix for the DNN model revealed a high true positive rate for heart disease predictions, demonstrating that the model effectively identifies at-risk individuals. In contrast, the CNN's confusion matrix showed a higher false negative rate, indicating a tendency to misclassify patients without heart disease as having the condition.

Table 2: Confusion matrix - DNN

	Predicted 0	Predicted 1	Predicted 2	Predicted 3	Predicted 4
Actual 0	57	18	0	0	0
Actual 1	9	45	0	0	0
Actual 2	1	24	0	0	0
Actual 3	0	26	0	0	0
Actual 4	0	4	0	0	0

From the matrix in Table 2, it is observed that the TP of DNN model correctly identified 45 true positives (TP) for heart disease risk (class 1). And True Negatives (TN) is accurately identified 57 true negatives (TN) (class 0). False Positives (FP) there were 18 false positives, indicating misclassification of patients without heart disease as having the condition. FN the model missed 9 actual cases of heart disease by incorrectly classifying them.

Table 3 : Performance of CNN

	precision	recall	f1-score	support
0	64	79	71	75
1	47	44	46	54
2	35	28	31	25
3	38	19	26	26
4	0	0	0	4

4.2.3 Performance of the Convolutional Neural Network (CNN) : In contrast, according to table 3 and fig 6 the Convolutional Neural Network (CNN) exhibited a lower accuracy of 45.11% (CNN Accuracy: 0.4511). While CNNs are typically well-suited for image data and spatial hierarchies, their performance on tabular data in this study was suboptimal. The precision for the CNN was calculated at 50.99%, meaning that when the CNN predicted a patient to be at risk of heart disease, there was a 50.99% likelihood of that prediction being correct. The recall for the CNN was measured at 45.11%, suggesting that it only correctly identified 45.11% of the actual positive cases. This indicates a significant limitation in identifying true positive cases, which is critical in clinical settings. Furthermore, the F1 Score for CNN was 37.90%, highlighting an imbalanced trade-off between precision and recall when compared to other models like the DNN.

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Fig 6: Performance of CNN

Table 4: Confusion matrix - CNN

	P 0	P 1	P 2	P 3	P 4
A 0	29	46	0	0	0
A 1	0	54	0	0	0
A 2	0	25	0	0	0
A 3	0	26	0	0	0
A 4	0	4	0	0	0

The confusion matrix in table 4 for the CNN model reveals a significant bias toward predicting Class 1 across most cases. While the model correctly identified 29 instances of Class 0, it misclassified 46 instances as Class 1. It performed perfectly for Class 1, predicting all 54 instances correctly. However, the model failed to correctly identify any instances of Classes 2, 3, and 4, as it misclassified all of them as Class 1. This highlights the model's inability to distinguish between these classes, likely due to class imbalance or limitations in the model's design, resulting in poor overall classification performance.

4.2.4 DNN Performance with SMOTE and Feature selection: The Deep Neural Network (DNN) achieved an impressive overall accuracy of 89.13%, showcasing its ability to effectively classify instances across most classes. The precision and recall metrics indicate that the model excels particularly in identifying Class 0 and Class 1, with precision scores of 89% and 83% and recall rates of 92% and 93%, respectively. However, the model's performance drops significantly for Class 2 and Class 3, which exhibit recall rates of 40% and 31% and F1-scores of 55 and 48. This discrepancy suggests that while the DNN can accurately identify certain classes, it struggles with minority classes, potentially due to their limited representation in the training dataset. Overall, the DNN demonstrates strong performance in handling more frequent classes but highlights challenges in detecting less common instances.

Table 5 Performance Metrics (DNN):

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Class	Precision	Recall	F1-Score	Support
0	89	92	91	75
1	83	93	88	54
2	87	40	55	25
3	100	31	48	26
4	75	75	75	4

Table 6 Confusion Matrix (DNN):

	P 0	P 1	P 2	P 3	P 4
A 0	69	6	0	0	0
A 1	4	50	0	0	0
A 2	0	15	10	0	0
A 3	0	18	0	8	0
A 4	0	1	0	0	3

4.2.5 CNN with SMOTE and Feature selection

In contrast, the Convolutional Neural Network (CNN) achieved a lower overall accuracy of 77.17%**,** indicating reduced effectiveness in classifying the data compared to the DNN. The CNN exhibited solid precision scores for Class 0 and Class 1 (84% and 75%, respectively), with recall rates of 80% and 94%**.** However, it struggled significantly with Class 2 and Class 3**,** which showed low recall rates of 28% and 27% despite relatively high precision (77% and 100%). This pattern suggests that while the CNN can accurately identify instances of certain classes, it fails to recognize many instances in other classes. The F1-scores for Classes 2 and 3 were particularly concerning, underscoring the model's difficulty in balancing precision and recall for these classes.

Table 7 Confusion Matrix (CNN):

	P 0	**P 1**	**P 2**	**P 3**	**P 4**
A 0	60	15	0	0	0
A 1	3	51	0	0	0
A 2	1	17	7	0	0
A 3	0	19	0	7	0
A 4	0	1	0	0	3

Table 8 Performance Metrics (CNN):

Class	Precision	Recall	F1-Score	Support
0	84	80	82	75
1	75	94	83	54
2	77	28	42	25
3	100	27	43	26
4	100	75	86	4

In summary, both the DNN and CNN exhibit varying strengths and weaknesses in their classification performance following SMOTE and feature extraction. The DNN demonstrates superior accuracy and a more balanced performance across classes, particularly excelling in identifying Class 0 and Class 1. Conversely, the CNN, while showing decent precision in some classes, fails to achieve a comparable level of accuracy, particularly for minority classes. Both models struggle with underrepresented classes, particularly Class 2 and Class 3, highlighting the ongoing challenges of class imbalance in machine learning. Future work may benefit from refining feature engineering, exploring advanced sampling techniques, or utilizing models better suited for multi-class classification problems.

5. Conclusion

This research investigated the potential of deep learning models, specifically Deep Neural Networks (DNN) and Convolutional Neural Networks (CNN), in predicting heart disease risk based on various clinical and demographic features. Through a comprehensive exploratory data analysis (EDA), significant correlations and patterns within the dataset were identified, providing a foundational understanding of the factors influencing heart disease. The results demonstrated that the SMOTE and Feature selection with DNN model outperformed the CNN in terms of accuracy, precision, recall, and F1-score, effectively classifying patients with and without heart disease. While the DNN showed promising results, it also highlighted challenges in accurately predicting certain classes, particularly those representing higher-risk categories. The CNN's lower performance emphasized the need for caution when applying models traditionally suited for image data to tabular datasets. Overall, this work underscores the importance of utilizing SMOTE and feature model selection and improvement strategies. The insights gained from this research can guide future efforts in enhancing deep learning applications in healthcare, ultimately contributing to better predictive models for heart disease risk management. Future work should focus on refining model performance through advanced techniques such as ensemble methods, hyperparameter tuning, and expanding the feature set to include additional relevant factors. By leveraging the potential of machine learning, enhance early detection and intervention strategies, ultimately improving patient outcomes and reducing the burden of heart disease in populations.

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