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Effect of Imbalance Data Handling Techniques to Improve the Accuracy of Heart Disease Prediction Using Machine Learning and Deep Learning

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Presented by

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Presentation Outlines

- 1. Introduction
- 2. Motivation and Objectives
- 3. Background Study
- 4. Method and Materials
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Introduction

- Approximately *17.9 million* people died of cardiovascular diseases (CVD) in each year according to WHO report, which is 32% of the fatality rate due to all death reasons. Heart disease is one of the life threatening CVD from the past few years.
- This study focuses on the <u>effect of different imbalance data</u> <u>handling techniques</u> to improve the classification accuracy of different machine learning and deep learning classifiers.







Motivation and Objective

Nowadays, heart disease is increasing at an alarming rate. Early stage heart disease prediction can help to take proper action to mitigate. The performance of the existing machine learning algorithms are good and different preprocessing techniques are already used in different studies. *Different imbalance data handling techniques have* an effect on the classification performance. To find out the effect, this study balances the dataset using different imbalance data handling techniques and predicts the heart disease. Also, the best imbalance data handling **techniques** for this type of analysis is found out.



To perform preprocessing techniques on the heart disease dataset to make it more trainable. To find the effect of different imbalance data handling techniques to the classification per-

formance of machine and deep learning learning classifiers.







Background Study

Rohit Bharti et al., in 2021 proposed a prediction of heart disease using a combination of machine learning and deep learning [1]. In this study they used a UCI heart disease prediction dataset. They apply Lasso feature selection technique. LR provided 83%, KNN provided 85%, SVM provided 83%, RF provided 80%, DT provided 82% and Deep Learning provided 94% accuracy.

Using feature selection to improve heart disease prediction was proposed by Ke Yuan et al. [2]. They proposed hybrid gradient boosting decision trees with logistic regression (HGBDTLR) ensemble technique. For this study they used Cleveland heart disease dataset and they got accuracy using DT 82%, RF 87%, KNN 64%, AdaBoost 85%, LR 85%, SVM 82%, GBDT 80%, HRFLM 89% and HGBDTLR 92%.

Saiful Islam et al., in 2020 proffered a cardiovascular disease forecast using machine learning paradigms [3]. They used UCI heart disease dataset and applied LR, SVM, DT and NB. Using LR 86%, SVM 84%, DT 75% and NB 74% accuracy they got.



Method and Materials



Cleveland Heart Disease Dataset:

Positive classes - 165(54.46%) and Negative classes - 138(45.54%)

Feature	Description	Feature	Description
age	Age measured in years	thalach	Maximum heart rate achieved
sex	1 = male, 0 = female	exang	Exercise induced angina
ср	Chest pain type: 1 = typical angina 2 = atypical angina 3 = non-anginal pain 4 = asymptomatic	oldpeak	ST depression induced by exercise relative to rest
trestbps	Resting blood pressure (in mm Hg on admission to the hospital)	slope	The slope of the peak exercise ST segment 1 = upsloping 2 = flat 3 = down sloping
chol	Serum cholesterol in mg/dl	ca	Number of major vessels (0-3) colored by fluoroscopy
fbs	Fasting blood sugar > 120 mg/dl 1 = true; 0 = false	thal	3 = normal 6 = fixed defect 7 = reversible defect
restecg	0 = normal 1 = having ST-T wave abnormality 2 = showing probable or definite left ventricular hypertrophy by Estes' criteria	Class	Diagnosis of heart disease (angiographic disease status) 0 = < 50% diameter narrowing 1 = > 50% diameter narrowing





Method and Materials

Imbalance Data Handling Technique

We employed several imbalance data handling techniques. These are listed below:

- 1. SMOTE
- 2. ADASYN
- 3. SMOTETomek
- 4. NearMiss

Classifier

For this study we employed six classifiers. These are listed below:

- Support Vector Machine (SVM)
- 2. Gaussian Naive Bayes (GNB)
- 3. Random Forest (RF)
- 4. Logistic Regression (LR)
- 5. Multilayer Perceptron (MLP)
- 6. LR-MLP Ensemble

Evaluation Metric

Several evaluation metric we used to measure the performance. These are listed below:

- 1. Accuracy
- 2. Precision
- 3. Recall
- 4. F-1 Score
- 5. Specificity
- 6. Cohen Kappa
- 7. AUC Score
- 8. ROC Curve





Method and Materials

Methodology Imbalanced Data Splitting Data Data **Balanced** Data ADASYN SMOTE Training Testing SMOTE NearMiss Tomek Accuracy Precision Recall Prediction Models F-1 Score Specificity Cohen Kappa AUC





Step 2 Data Processing

Step 3 Imbalance data handle

Step 4

Training and Testing



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Performance Evaluation Step 6 Result and discussion





Result Analysis

Algo	orithm	Accuracy	Preci- sion	Recall	F-1 Score	Specifi- city	Cohen Kappa	AUC	aset	Algorithm	Accuracy	Preci- sion	Recall	F-1 Score	Specifi- city	Cohen Kappa	AU
sv	VM	95%	0.95	0.95	0.95	0.92	0.9	0.96	d Dat	SVM	96%	0.96	0.96	0.96	0.94	0.91	0.
LR-I	MLP	92%	0.92	0.92	0.92	0.88	0.83	0.96	lance	LR-MLP	96%	0.96	0.96	0.96	0.97	0.91	0
L	LR	92%	0.92	0.92	0.92	0.88	0.83	0.96	ek Ba	LR	94%	0.94	0.94	0.94	0.97	0.88	0
Gì	NB	90%	0.9	0.9	0.9	0.88	0.8	0.94	ETom	GNB	94%	0.94	0.94	0.94	0.97	0.88	0
М	ILP	90%	0.9	0.9	0.9	0.92	0.8	0.96	MOTI	MLP	96%	0.96	0.96	0.96	0.97	0.91	0
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orm Algo	nanco	89% e on ba Accuracy	0.89 alanc Preci- sion	0.89 ed da Recall	0.89 Ita us F-1 Score	0.84	0.76 IOTE Cohen Kappa	0.94 AUC	Perf	RF Ormanc Algorithm	94% e on ba Accuracy	0.94 alanc Preci- sion	0.94 ed da Recall	0.94 ata us F-1 Score	0.97	0.88 DASYN Cohen Kappa	0
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Result Analysis



aset	Algorithm	Accuracy	Preci- sion	Recall	F-1 Score	Specifi- city	Cohen Kappa	AUC
Dat	SVM	84%	0.85	0.84	0.84	0.92	0.68	0.9
nced	LR-MLP	90%	0.9	0.9	0.9	0.92	0.8	0.94
Bala	LR	86%	0.86	0.86	0.86	0.88	0.72	0.93
Aiss	GNB	82%	0.8	0.8	0.8	0.84	0.6	0.89
lear	MLP	88%	0.88	0.88	0.88	0.92	0.76	0.92
Z	RF	86%	0.87	0.86	0.86	0.92	0.72	0.91

Result are shown by the bar chart and

ROC curve.









Conclusion and Future Works

CONCLUSION

- □ This analysis mainly focuses on the *effect of different imbalance data handling techniques* to improve the accuracy to predict the heart disease using Cleveland dataset. Most of the cases SVM performs well than other models.
- In imbalance data most of the algorithms shows greater than or equal to 89% accuracy. But, using SMOTETomek imbalance data handling techniques, all the algorithms <u>shows greater than or equal</u> to <u>94% accuracy.</u>
- Also performance of SMOTE (Oversampling), ADASYN (Oversampling) is better than imbalance data but the performance of NearMiss (Under sampling) is too low compared to other techniques.

FUTURE WORKS

- □ Feature selection and dimensionality reduction may improve the analysis in this sector.
- Hybrid and Ensemble technique may also improve the accuracy level of prediction.
- □ Deep learning algorithms plays a vital role in the field of healthcare. Other deep learning algorithms may give better outcome.





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Thank You

Question & Answer