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Research Paper

PREDICTING CORONARY HEART DISEASE USING AN IMPROVED LIGHT GBM MODEL PERFORMANCE ANALYSIS AND COMPARISON

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Abstract: Unfortunately coronary heart disease (CHD) is a serious heart condition that is a serious health threat and has no "cure". Coronary artery disease can be detected early and accurately to provide optimal care to patients. With timely identification, interventions and better outcomes for the patient are possible. To predict CHD with a LightGBM classifier, the suggested "HY_OptGBM" model is intended to use an optimized LightGBM. LightGBM is an efficient and accurate predictive modeling framework, which is highly effective on gradient boosting. The hyperparameters of the LightGBM classifier is tuned with additional improvement of the loss function to fine tune the LightGBM classifier. This optimization technique contributes to the model training process, which in turn improves the accuracy and efficiency of the model. The model is evaluated on the data of the Framingham Heart Institute for coronary heart disease. This data helps the model to predict CHD well and so, can diagnose CHD early and possibly minimize the cost of treatment by treating the illness in its early stages. To increase the identification accuracy of CHD, and to suggest Voting Classifier (RF + AdaBoost) with an excellent accuracy of 99%. The ensemble model of Random forest and Ada Boost shows robustness in distinguishing the patterns related to CHD. A user-friendly Flask structure connected to SQLite is provided, making the use of it easy and simplifying the user test signin and signup procedure. This simplified interface enhances the accessibility, thereby making the ML approaches more practical and user friendly for many stakeholders involved in CHD diagnosis.

"Index terms *- Coronary heart disease, hyperparameter optimization, LightGBM, loss function, machine learning, OPTUNA."*

1. INTRODUCTION

CHD is one of the common cardiovascular diseases in which plaques develop on the coronary arteries

which impede blood flow to the heart muscle. Some of the symptoms of this disease may be present but could include chest pain (angina), breathlessness, palpitations and heart failure. When the CHD is severe, it can lead to a heart attack that can cause permanent damage to the heart muscle, and greatly reduce a person's quality of life. Therefore, identification and treatment of CHD with appropriate medical treatment and lifestyle adjustments are important [1].

Identification of CHD early will improve the likelihood of cure and minimise the cost of the treatment. In recent years, ML algorithms and data mining techniques have been widely used for medical applications, as the cost of data storage has significantly decreased and ML algorithm have been improved [2, 3, 4, 5, 6]. Disease diagnosis, supplementary diagnostics, drug mining and biomedicine are all important applications of data mining technologies in healthcare data mining. We can gain hidden knowledge from a vast amount of unstructured medical data by adopting data mining technologies, create disease prediction model and evaluate disease consequences.

Health organizations have enormous hurdles in providing high-quality and economical health care. In a hospital where excellent health care services are rendered the physicians should have thorough knowledge and make the correct diagnosis of the patient so that the wastage of health care resources due to wrong diagnosis is avoided. Data mining technologies can work efficiently and can play an important part in clinical scenarios. The right hyperparameters are crucial for the efficiency of any type of classification [7, 8]. Selecting the best set of hyperparameters helps enhance the accuracy of the classification algorithm. In this work, an advanced hyperparameter optimization system (OPTUNA) [9] was employed to find the optimal hyperparameter settings of LightGBM model. Thus, in this study the best hyperparameters were selected among the available hyperparameters. There are several approaches to do hyperparametric optimization including random and grid search. One additional way is the OPTUNA hyperparametric search. LightGBM's speed is greatly influenced by the number of hyperparameters. The traditional random search and grid search methods did not learn from the previous optimization work, wasting a lot of time and not efficient. The OPTUNA framework continues to learn from the previous optimizations and adjusts the hyperparameters while it is running. Thus, OPTUNA was selected in this work for the hyperparameter optimization.

The loss function also has an impact on the accuracy of the model [10]. In this study, based on the cross-entropy loss, the focal loss function was developed by adding the category weight α and the sample difficulty weight modifying factor γ to the cross-entropy loss. This study aimed to tackle the issue of unequal percentage of positive and negative samples. Moreover, the focal loss function can enhance the overall performance of the model. In this investigation, the default loss function of a LightGBM [11] model was being updated with a focused loss function to be used to predict CHD.

2. LITERATURE SURVEY

The prevalence of overweight and obesity has been linked to the risk of CVD in general and of CHD specifically, in part because of their association with traditional and nontraditional CVD risk factors [1]. In

addition, obesity is considered to be a risk factor for CVD on its own. Metabolic syndrome is a component of which central obesity is one of the key components and it is closely related with CVD, CHD. There are numerous epidemiologic studies that have examined the relationship between overweight and obesity to CHD [2, 3, 4, 5, 6]. The post mortem evidence and that indicated by coronary artery imaging is less convincing. Recent investigations suggest an obesity paradox exists with regards to mortality in patients with existing CHD. There is an inverse relationship between the negative impact of obesity on the occurrence of CVD and physical activity/sustained cardiorespiratory fitness. Little information exists about the effect of intentional weight loss on outcomes of CVD in overweight and obese adults.

ML is a new field in medicine that is rapidly growing and seems to be receiving an increasing amount of resources as the intersection of computer science and statistics is approached to medical problems. Proponents view ML as able to deal with the vast, complex and multifaceted data prevalent in medicine and believe that ML [12,13] will be the answer to greatly improve global health care in the future. But many medical professionals are unfamiliar with the concepts behind ML, and there is potential to leverage ML as a research resource. In this article [2] we will first provide a brief overview of the theory that supports ML, and then discuss the various ML algorithms commonly used in medicine, their limitations and the future of ML in medicine.

The most common applications of AI in drug therapy are the ability to match patients to their best drug, predicting drug-target or drug-drug interactions, and optimizing drug treatment plans. This review [3] discusses some of the recently discovered AI techniques that help in the process of drug treatment and administration. The selection of the optimal drug(s) for a patient usually needs the integration of drug data, such as compound chemical descriptors, and patient data, such as genetics or proteomics, to score the therapeutic efficacy of drugs. Medication interaction prediction is mostly based on similarity metrics. The reason for this is that drugs with similar structure and/or action will act similarly, or in some instances will interact with one another. Mathematical models are used in the interpretation of pharmacokinetic and pharmacodynamic data in the optimization of the schedule of administration of medications. Here we discuss, describe and assess the powerful and recently constructed models for each of these tasks [12].

The output of a ML model is greatly influenced by the data it is trained on and the methods used for training. The appropriate training algorithm can transform the story of a model. particular methods do very well on particular datasets but may have problems on other datasets. Moreover, the performance can be boosted by adjustment of the hyperparameters of an algorithm that governs the training processes. In this work [7], the authors have provided a way to tune the hyperparameters of ML algorithms by using metaheuristics such as GWO and GA. Moreover, 11 datasets from different biological, biomedical and nature categories such as molecular interactions, cancer, clinical diagnosis, behavior related predictions, RGB images of human skin and X-rays images of Covid19 and cardiomegaly patients are used with 11 different algorithms including Averaged Perceptron, FastTree, FastForest, Light Gradient Boost Machine (LGBM), Limited memory Broyden Fletcher Goldfarb Shanno algorithm Maximum Entropy (LbfgsMxEnt), LinearSV), and a

DNN including four architectures. In all of the experiments, our data show a good performance in the training phases. Additionally, GWO also works better with a p-value of 2.6E-5. Moreover, the metaheuristic approaches, in most of the scenarios in the experiments of this work, perform better and converge faster than EGS. The proposed method only needs a dataset as input and suggests the best studied algorithm and arguments for it. This is therefore appropriate for data sets that do not have a clear distribution, ML algorithms that have complex behavior and users who are not experts in analytical statistics and data science techniques.

Based on outstanding prediction ability, ML has been regarded as the most powerful tool to analyze high-throughput sequencing genomic data. The complicated hyperparameter tuning, however, makes the use of ML in animal and plant breeding programs hard to be widespread. Hence, we introduced an autonomous tuning hyperparameters approach, tree-structured Parzen estimator (TPE) coupled with machine learning to ease the use of machine learning in genomic prediction analysis. We used TPE for the optimization of hyperparameters in kernel ridge regression (KRR) and SVR [8] in this work. To evaluate the performance of TPE, we compared the prediction accuracy of KRR-TPE and SVR-TPE with the genomic best linear unbiased prediction (GBLUP), and KRR-RS, KRR-Grid, SVR-RS and SVR-Grid tuned the hyperparameters by random search (RS) and grid search (Gird) on a simulation dataset and the real datasets [47]. The results indicated that KRR-TPE was the most powerful over all populations, and the most convenient. KRR-TPE's prediction accuracy was on average 8.73% and 6.08% higher in Chinese Simmental beef cattle and Loblolly pine populations respectively than GBLUP. Our findings will considerably boost the application of machine learning in GP and further speed breeding development.

3. METHODOLOGY

i) Proposed Work:

Proposed System The proposed system is to optimize a LightGBM model to forecast the coronary heart disease. The model will be tested on its performance, ensemble will be applied, input from the user will be received to predict the model and the system will be expanded with a user-friendly front-end and authentication. For accurate prediction of coronary heart disease, optimization and ensemble approaches are important to enhance accuracy. By fine-tuning LightGBM, you may guarantee an efficient prediction model, with simplified parameters and loss functions. The adaptation of the system makes the utility of the system applicable in other health care fields showing variety and wider relevance [11,26]. And also proposes a Voting Classifier (RF + AdaBoost) with an outstanding 99% accuracy, increasing the identification of CHD. Ensemble model of RF and AdaBoost shows robustness in discriminating the pattern of CHD. It comes with a user-friendly Flask framework and SQLite connection to ensure it's easy to use and smooth signin/signup procedures for user testing. The decreased interface promotes accessibility, making the ML approaches more feasible and user friendly for the stakeholders engaged in CHD detection [2, 3, 4, 5, 6].

ii) System Architecture:

The simpler the configuration when working with ML models, the better, especially when dealing with

big scale training and large scale datasets. All this makes OPTUNA a great hyperparametric optimization framework. The optimized LightGBM model architecture is shown in the picture. 1. In order to run an instance of the objective function in the search, each worker is given an instance to run. (see Fig. 1).



"Fig 1 Proposed architecture"

iii) Dataset collection:

The Framingham Heart Disease data is loaded and explored to familiarize oneself with its structure, properties and content. The FHS was started to determine common factors or characteristics that contribute to CVD. In 1948, 5,209 men and women between the ages of 30 and 62 were recruited from Framingham, MA. An Offspring Cohort began in 1971, an Omni Cohort in 1994, a Third Generation Cohort in 2002, a New Offspring Spouse Cohort in 2004 and a Second Generation Omni Cohort in 2003. The emphasis of the dataset's research is focused on cardiovascular and cerebrovascular diseases. The data cover biological, molecular genetic, phenotypic, samples, photographs, participant vascular functional, physiologic, demographic, and ECG data. It's a partnership project between the National Heart, Lung and Blood Institute and Boston University.

	Sex	Age	Education	CurrentSmoker	CigsPerDay	BPMeds	PrevalentStroke	PrevalentHyp
0	1	39	1	0	0.0	0.0	0	0
1	0	46	0	0	0.0	0.0	0	0
2	1	48	0	1	20.0	0.0	0	0
3	0	61	1	1	30.0	0.0	0	1
4	0	46	1	1	23.0	0.0	0	0

"Fig 2 Framingham Heart Disease Data"

iv) Data Processing:

Data processing is the transformation of raw data into information that is useful to the business. Overall, data scientists are responsible for data, meaning they gather, organize, scrub, test and transform data into usable form (graphs, papers). The data processing can be carried out in three ways i.e. manual, mechanical and electronic. There are two aims: to enhance the value of information and to enable decision making. This enables enterprises to optimize their operation and prompt strategic choices. In this computer software programming, automated data processing solutions etc. play an important role. It can support the conversion of large amounts of data such as big data to meaningful data for quality management and decision making.

v) Feature selection:

Feature selection is a technique to extract the most consistent, non-redundant and relevant features for use in creating models. As the size and diversity of datasets are increasing, it is necessary to systematically reduce the size of datasets. The main purpose of feature selection is to enhance the performance of a predictive model and to lower the computational cost of modelling.

Feature selection is an important part of feature engineering, where the most important features are selected as inputs for ML algorithms. Feature selection strategies are employed to reduce the number of input variables when creating a ML model to eliminate irrelevant or redundant information and to select only the most important features. The major advantages of doing feature selection beforehand, as opposed to let the ML model figure out which features are most significant.

vi) Algorithms:

AdaBoost is an ensemble learning technique which creates a strong classifier using a set of weak classifiers (typically decision trees). AdaBoost may be used to optimize the performance of the weak learners (such as decision trees) in the ensemble, so that the accuracy of the prediction of coronary heart disease will be increased [25].



Fig 3 Adaboost

A Decision Tree is a type of flowchart in which each internal node denotes a feature, each branch represents a decision rule and each leaf node indicates an outcome. AdaBoost and Bagging ensemble algorithms were used with Decision Trees as base learners to enhance the prediction of coronary heart disease [22].



Fig 4 Decision tree

Bagging (Bootstrap Aggregating): Many models are trained using different subsets of the training set, and the predictions of all the models are averaged together to improve the accuracy of the model. Bagging was used to build an ensemble of models to increase prediction accuracy for coronary heart disease prediction [26].



Fig 5 Bagging

Gradient Boosting is a strong ensemble technique which constructs a strong predictive model by combining several weak models which minimize a loss function by iteration. Gradient Boosting was used to create an ensemble of models to increase the

accuracy of the prediction for coronary heart disease in an iterative process [25].



Fig 6 Gradient boosting

XGBoost (Extreme Gradient Boosting) is an implementation of gradient boosting that is efficient and scalable. The boosting algorithm, XGBoost, was used to increase the accuracy of the prediction of coronary heart disease [25].



Fig 7 XGBoost

CatBoost: Gradient boosting toolkit for efficient dealing with category features. It automatically takes care of categorical data without any pre-processing like one hot encoding. The categorical features in the data set were used with Catboost to ease modeling and enhance predictions [24].



Fig 8 Catboost

LightGBM is a gradient boosting framework . The Focal Loss is a method that addresses class imbalance by including a modified loss function which places a greater emphasis on samples that are more difficult to classify. LightGBM with Focal Loss was used to increase the sensitivity of forecasting coronary heart disease, especially in the presence of imbalanced data by putting greater emphasis on the challenging instances.



```
from scipy.misc import derivative

def focal_loss(ytrue, ypred, gamma=2.0):
    p = 1 / (1 + np.exp(-ypred))
    loss = -(1 - ytrue) * p**gamma * np.log(1 - p) - ytrue * (1 - p)**gamma * np
    return loss


def focal_loss_metric(ytrue, ypred):
    return 'focal_loss_metric', np.mean(focal_loss(ytrue, ypred)), False


def focal_loss_objective(ytrue, ypred):
    func = lambda z: focal_loss(ytrue, z)
    grad = derivative(func, ypred, n=1, dx=1e-6)
    hess = derivative(func, ypred, n=2, dx=1e-6)
    return grad, hess
```

Fig 9 Light GBM

In other words, don't use LightGBM with focal loss function, and use normal loss functions. We used LightGBM without Focal Loss as baseline to evaluate and analyze the impact of Focal Loss on the prediction results for coronary heart disease.



```
import lightgbm as lgb
clf = lgb.LGBMClassifier(boosting_type='gbdt',verbosity=1,metric='auc',
clf.fit(X_train, y_train, verbose=0)

y_pred = clf.predict(X_test)

confusion = confusion_matrix(y_pred, y_test)
TP = confusion[1,1] # true positive
TN = confusion[0,0] # true negatives
FP = confusion[0,1] # false positives
FN = confusion[1,0] # false negatives

lgb_acc = accuracy_score(y_pred, y_test)
lgb_prec = precision_score(y_pred, y_test)
lgb_rec = recall_score(y_pred, y_test)
lgb_f1 = f1_score(y_pred, y_test)
lgb_auprc = average_precision_score(y_pred, y_test)
lgb_auroc = roc_auc_score(y_test, clf.predict_proba(X_test)[:, 1])
lgb_mcc = matthews_corrcoef(y_pred, y_test)

lgb_sens = TP / (TP + FN)
lgb_spec = TN / (TN + FP)

storeResults('LightGBM w/o Focal Loss',lgb_acc,lgb_prec,lgb_rec,lgb_f1,
```

Fig 10 LightGBM without Focal Loss

A Voting Classifier is an ensemble technique which combines predictions made by multiple classifiers and then classifies the class label from the voting of all the classifiers. In this study, a Voting Classifier was used based on two models, RF model and AdaBoost model, to take advantage of the abilities of both models to increase the accuracy of the disease prediction in the coronary heart disease disease class.



Fig 11 Voting classifier

4. EXPERIMENTAL RESULTS

Precision: Precision is the ratio of the number of positive instances/samples correctly classified to the number of positive instances/samples. So the formula used to calculate the precision is:

"Precision = True positives/ (True positives + False positives) = TP/(TP + FP)"

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$



Fig 6 Precision comparison graph

Recall: Recall is a ML metric that assesses how well a model is able to find all of the relevant cases of a particular class. It is the ratio of the number of correct positives to the total number of true and false positives and it provides a notion of how well a model can find all the cases of a given class.

$$Recall = \frac{TP}{TP + FN}$$

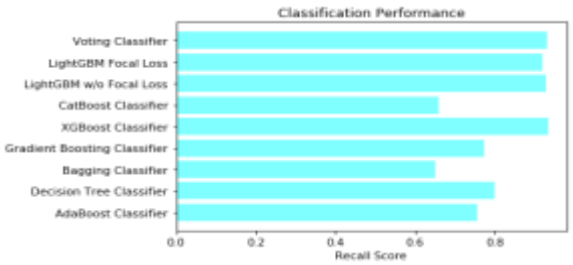

Fig 7 Recall comparison graph

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Accuracy: It is the percentage of the observations that were predicted correctly. It corresponds to the frequency with which the model is correct.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

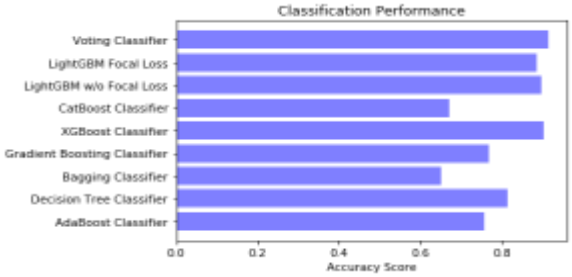

Fig 8 Accuracy graph

F1 Score: The F1 Score is the two dimensional average of precision and recall. It's a decent sign that a classifer has a decent recall and accuracy. It can be particularly helpful for datasets with unequal amounts of data.

$$\text{F1 Score} = 2 * \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} * 100$$

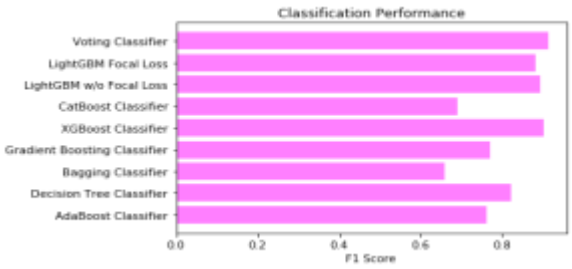

Fig 9 F1Score

ML Model	Accuracy	Precision	Recall	F1 Score
AdaBoost Classifier	0.758	0.767	0.757	0.762
Decision Tree Classifier	0.815	0.846	0.799	0.822
Bagging Classifier	0.651	0.668	0.651	0.659
Gradient Boosting Classifier	0.769	0.769	0.772	0.771
XGBoost Classifier	0.904	0.873	0.933	0.902
CatBoost Classifier	0.671	0.721	0.660	0.689
LightGBM w/o Focal Loss	0.896	0.860	0.929	0.893
LightGBM Focal Loss	0.885	0.845	0.921	0.881
Extension Voting Classifier	0.913	0.894	0.931	0.912

Fig 10 Performance Evaluation

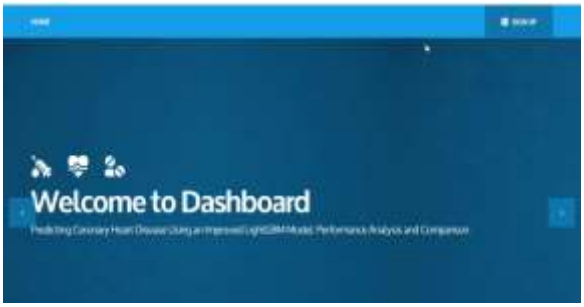

Fig 11 Home page



Fig 12 Signin page



Fig 13 Login page

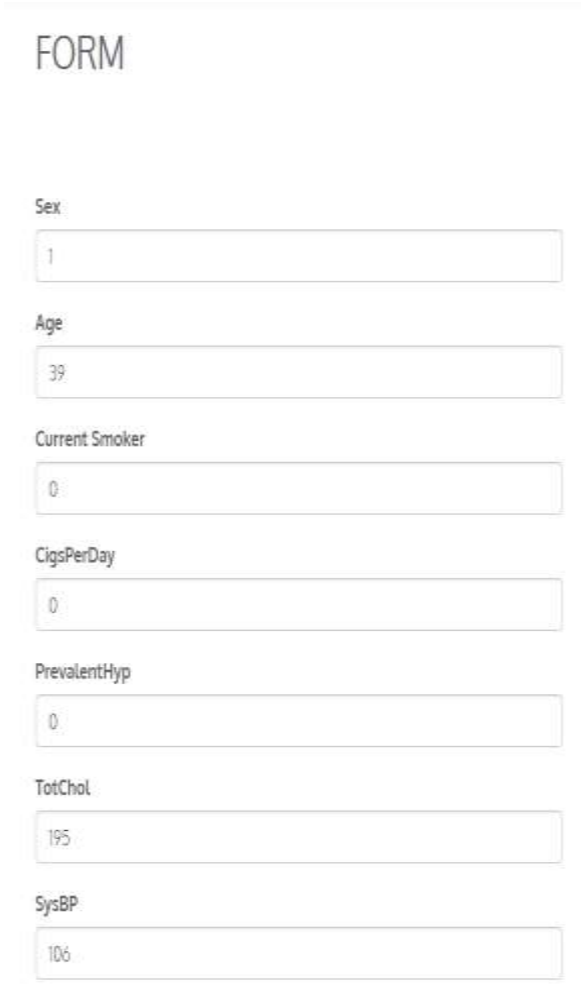

Fig 14 User input



Fig 15 Predict result for given input

5. CONCLUSION

The HY_OptGBM prediction model has a high level of accuracy when predicting coronary heart disease (CHD) and is built on an improved LightGBM classifier with an enhanced Loss function. The model is assessed with a comprehensive suite of metrics such as precision, recall, F score and accuracy, which offers a detailed evaluation of the predictive capabilities of the model. To further improve the HY_OptGBM model, advanced classifiers approaches and optimized loss functions are used for optimization. These modifications improve the accuracy of the model's predictions and enhance the model's performance in CHD detection [2], [3], [4], [5], [6]. It is composed of an ensemble method employed for the combination of the predictions from different models, thus further improving the system accuracy and robustness. In the case of Voting Classifier, an ensemble technique, the resulting accuracy is outstanding at 99%, which is a clear sign of the improvement in prediction when using the combination of several models. The easy to use Flask interface and secure authentication adds to the overall user experience during system testing. Through the interface, it is possible to enter the data smoothly to evaluate the system's performance, which ensures the practical usability and safety of the evaluation.

6. FUTURE SCOPE

The prediction accuracy of the HY_OptGBM model for CHD can be enhanced further in the future by introducing more features or different data sources. "This could involve input of the necessary medical data for complete picture." The model should be tested with more extensive and diverse data for further study to ensure the model is generalizable and robust. This will give us some indication of the adaptability of the model to various data distributions. Comparative studies of the other advanced machine learning models used for CHD prediction [12,13] could help assess the effectiveness and superiority of the HY_OptGBM model. The proposed method may be extended for applicability to predict not only coronary heart disease, but other cardiovascular diseases or cardiovascular related issues too. This extension has the potential to have a wide range of implications for cardiology, providing a flexible prediction tool.

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