Leveraging AutoML to provide NAFLD screening diagnosis: Proposed machine learning models

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Abstract

NAFLD is reported to be the only hepatic ailment increasing in its prevalence concurrently with both; obesity & T2DM. In the wake of a massive strain on global health resources due to COVID 19 pandemic, NAFLD is bound to be neglected & shelved. Abdominal ultrasonography is done for NAFLD screening diagnosis which has a high monetary cost associated with it. We uti- lized MLjar, an autoML web platform, to propose machine learning models that require no coding whatsoever & take in only easy-to-measure anthropometric measures for coming up with a screening diagnosis for NAFLD with considera- bly high AUC. Further studies are suggested to validate the generalization of the presented models.

Keywords: nafld; fatty liver disease; automl; machine learning; extreme gradient boosting; xgboost; lightgbm; random forest; regularized greedy forest

1.Introduction

Hepatic diseases taking the lives of as many as 1.75 million people worldwide annual- ly are a menace to be reckoned with.(1) Younossi ZM et al(1) indicated that non- alcoholic fatty liver disease (NAFLD) is the only hepatic pathology growing exponen- tially in its prevalence, in coincidence with the increasing rates of both; obesity as well as type 2 diabetes mellitus (T2DM): all wreaking havoc.(2)(3)(4) Where COVID-19 pandemic is undeniably encroaching over the global health system's resources, NAFLD, along with other ailments, is bound to be ignored which may lead to a rise in the associated morbidity & mortality.

A considerable amount of financial resources are being put in globally in the fight against COVID-19 pandemic where radiological diagnosis for NAFLD demands a considerable allocation of funds, the prioritization of resources shall undeniably end up in missing cases on the cost of the patients as well as their families in terms of the psychological burden. A low-cost, accurate system to screen patients for a potential NAFLD diagnosis using simple, easy-to-measure anthropometric measures is a dire need of time, thus. Huang BX et al, in a cross-sectional study conducted in the Health Examination Center in Guangzhou, China took in anthropometric measures & abdominal ultraso- nography & concluded neck circumference to be an independent predictor for the fatty liver disease. (5) The purpose of this study is to create such machine learning models that take in the said easy-to-measure variables from the Huang BX et al study (5) & come up with an autoML protocol for initial screening diagnosis for NAFLD: models that are, if not having a potential to replace, should be at least comparable with the abdominal ultra- sound screening diagnosis for NAFLD. By adopting Mljar(6), a zero-code autoML web platform providing feature preprocessing and eningeering, algorithm training and hyperparameters selection bundle for machine learning, we are able to create such practical models.

Materials & Methods

Study Cohort

The study takes in data (7) from Huang BX et al. (5). The authors took in 4053 subjects, 2436 men and 1617 women between 20 and 88 years of age, after excluding those patients that had a history of co-morbid conditions as well as those with a lack of heaptic ultrasonography data. Patients' history records were inquired & state-of-the- art methods were adopted to measure anthropometric & biochemical variables leaving negligible measurement errors, only. Contrary to South Asian standards where BMI of ≥ 25 Kg/m2 is termed as Overweight, a BMI ≧24 kg/m2, for both genders, is termed as Overweight by Huang BX et al. (5), citing Zhou B (8). The Graif's criteria (9) was adopted to diagnose Fatty liver disease on ultrasonography.

Statistical analysis Development of Models

Homogenous Development Framework MLjar(6), an AutoML zero-code machine learning web platform, is a complete pack- age for data loading, pre-processing, modelling & result interpretation with a consid- erably high quality of machine learning models which can be deployed both locally & across a rest API.

A homogenous approach (Table 1) was adopted for the development of the models vis-à-vis the preprocessing & tuning protocols as well as system specifications so as to keep the model development bias to a minimum.

Development framework	Features
Preprocessing protocol	One-hot encoding to convert categorical features
System specifications	8 CPUs, 15 GB RAM
Tuning protocol • Validation type • Tuning mode • Time limit for single model	15-fold cross-validation, Shuffling of samples & stratification of classes in folds Perfect mode (25-35 models) 5 minutes

Table 1. Homogenous Development Framework

Models developed

Henceforth mentioned machine learning models were, thus, created:

- Extreme Gradient Boosting (Xgboost)
- LightGBM (LGBM)
- Random Forest (RF)
- Regularized Greedy Forest (RGF)
- Extra Trees (ET)
- k-Nearest Neighbor (KNN)
- Logistic Regression (LR)
- Neural Network (NN)

Outcome variables

Since the class imbalance was considerably high, the discriminative ability of the models were the primary outcome variables. AUC-ROC analysis was adopted to measure that ability.[10] The respective values were interpreted in accordance with the schema provided by Lau L et al.[10] **(Table 2)**

AUC-ROC value	Interpretation
>0.9	Excellent discrimination
>0.75	Good discrimination
>0.5	Random guessing

Table 2. Interpretation of the AUC-ROC analysis (Adopted from: Lau L et al.) (AUC-ROC: Area under the receiver operating characteristic curve)

Secondarily, training time was also analyzed. Ideally, the best model shall be the one that has the highest discriminating capacity & yields results within the smallest time period.

Results

Algorithm performances

The study adopted a zero-code ML platform to come up with 8 types of machine learning models that take in easy-to-measure anthropometric measures such as BMI & waist-to-hip ratio in order to provide a screening diagnosis for NAFLD.

As indicated in table 3, all of the algorithms, trained in accordance with the afore- mentioned Homogenous Development Framework, have good discriminating ability to designate the dichotomous variable of interest.

RF came out to have the highest discriminating ability, with a computation time of 4 minutes 9 seconds. Out of the proposed models, KNN had the least AUC but a con- siderably less computation time of only 6 seconds. LGBM required as much as 10 minutes to come up with a considerable AUC. LR completed its computation in the least amount of time.

Among the ensemble averages, RGF achieved the highest average. Given that the best model of RGF was up with its training in only 10 seconds & an additional 35 seconds were lapsed for ensemble averaging, RGF outperforms all others models by achieving the highest AUC & thus exhibiting the best discriminating ability out of all the models.

KNN exhibited the lowest ensemble average. (Ensemble average of LGBM & NN was not calculated.) Thus, it is safe to indicate that KNN underperformed the most out all the proposed models.

Algorithm	Area under Curve	Time	Ensemble Averaging	Time
Xgboost	0.822004	0:07:45	0.822679	0:00:35
Lgbm	0.823532	**0:10:05**	-	-
Rf	**0.824809**	0:04:09	0.825137	0:00:33
Rgf	0.823396	0:00:10	**0.826389**	0:00:35
Et	0.823557	0:01:02	0.824575	0:00:35
Knn	**0.815769**	0:00:06	0.816616	0:00:28
Lr	0.821363	**0:00:01**	0.821632	0:00:26
Nn	0.820271	0:03:16	-	-

Table 3. AUC & training time of the proposed models

Discussion

Many studies have been done to utilize machine learning for the prediction of fatty liver disease. Atabaki-Pasdar N et al [11] in a major modelling & validation study con- cluded that the highest AUC (of 0.84 for the respective study) is obtained by the com- bination of "-omics" data & clinical variables. Using MRI-derived proton density fat fraction for referencing, Han A et al (12) developed deep learning one-dimensional convolutional neural networks for NAFLD diagnosis by taking in ultrasound data.1 By taking in all the patients who had been screened for fatty liver at the New Taipei City Hospital between the 1st and 31st of December 2009, Wu CC et al (13)

developed several classification models to predict fatty liver disease and obtained the highest AUC of 0.925 on a Random Forest model. Feature selection was employed to obtain the best variables to be fed in the models, here. The utilization of machine learning to predict hepatic pathologies in general & NAFLD in particular is thus evident.

Our proposed models are the very first effort, to the best of our knowledge, to lev- erage autoML zero-code platforms to come up with machine learning models that are trained to have a good discriminating ability to predict NAFLD using only anthropo- metric measures. The proposed models neither require costly analysis so that varia- bles, such as unltrasonographic signals,

may be fed in them to obtain a prediction nor does it require considerably high computation time & resources.

This been stated, the model does require external validation using data from popu- lations different from its training population. Only thus can a machine learning mod- el's generalization can be truly validated. Moreover, a study comparing the presented model's diagnosis with an abdominal ultrasound diagnosis for NAFLD, the predic- tions assessed against hepatic biopsy, is proposed to be in order to explore the pre- sented models' potential to replace abdominal ultrasound as an initial diagnostic tool for NAFLD.

Since autoML platform was adopted, the proposed models are analogous to a black-box, the internal workings of which are difficult to decipher. Moreover, the computation time of the best LR model is only 1 second which might possibly be due to overfitting of the respective model.

The presented models indicate that the fusion of machine learning & medicine is fruitful for cutting down the associated costs of screening and initial diagnosis of NAFLD: an ailment that has considerable morbidity and mortality associated with it.For the Han A et al (12) study, the metrics against which the respective proposed model was evaluated did not include AUC.

Conclusion

By adopting an autoML zero-code platform, machine learning models with good dis- criminating ability are presented that require only easy-to-measure anthropometric measures as input variables to come up with an initial screening diagnosis for NAFLD. Further studies should be conducted to compare the proposed models with abdominal ultrasound for the screening diagnosis of NAFLD.

Potential Conflict of Interest

The authors report no potential conflict of interest whatsoever.

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Study Association

This study is neither associated with any thesis or dissertation work nor with any con- ference.

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