International Multidisciplinary Research Journal Reviews (IMRJR)

International Multidisciplinary Research Journal Reviews (IMRJR)
A Peer-reviewed journal
Volume 2, Issue 9, September 2025
DOI 10.17148/IMRJR.2025.020905

Enhancing Prediction Accuracy Using Machine Learning Techniques in Identifying Fatty Liver Disease

A. Sahaya Mercy[1], Dr. G. Arockia Sahaya Sheela[2]

PhD Scholar (Full Time), Department of Computer Science, St. Joseph's College (Autonomous), Tiruchirappalli-2, Affiliated to Bharathidasan University, Tamil Nadu, India[1]

Assistant Professor, Department of Computer Science, St. Joseph's College (Autonomous), Tiruchirappalli-2, Affiliated to Bharathidasan University, Tamil Nadu, India[2]

Abstract: One of the main causes of liver-related morbidity in the world today is Fatty Liver Disease (FLD), which includes both Alcoholic Fatty Liver Disease (AFLD) and Non-Alcoholic Fatty Liver Disease (NAFLD). There are effective intervention and prevention of serious liver disorders, such as cirrhosis and liver cancer, which depend on the early and accurate detection of Fatty Liver Disease (FLD). Liver biopsies and other traditional diagnostic techniques are intrusive and frequently unfeasible for widespread screening. To enhance the prediction accuracy of detecting FLD through clinical, biochemical and imaging data, this study explores the application of Machine Learning(ML) techniques. The research investigates into advanced methodologies for processing medical imaging data, encompassing diverse data pre-processing strategies, feature selection approaches and model training techniques which include ensemble methods such as Random Forest, Gradient Boosting and XGBoost and deep learning techniques. Further regularization and resampling approaches are used to address the issues of over fitting and class imbalance. Higher accuracy, precision, recall, and F1 scores compared to conventional techniques show how the combination of strong feature engineering, hyper parameter tweaking, and sophisticated ML models greatly improves diagnostic performance. The present paper establishes the groundwork for further research in predictive health analytics and demonstrates the promise of ML-driven methods in clinical settings for non-invasive, precise and scalable FLD identification.

Keywords: Machine Learning, Supervised Learning Algorithms, Image Mining Techniques, Fatty Liver Disease, Accuracy.

I. INTRODUCTION

The term "Fatty Liver Disease" (FLD) refers to a group of disorders that include cirrhosis, Non-Alcoholic Steato Hepatitis (NASH), and simple steatosis. Due to factors including obesity, a sedentary lifestyle, and poor eating habits, FLD is becoming more and more common worldwide. Prompt diagnosis and treatments are crucial in halting disease and its related consequences, such as hepatocellular carcinoma as well as hepatic failure. The Fatty liver disease in humans is depicted in Figure 1.

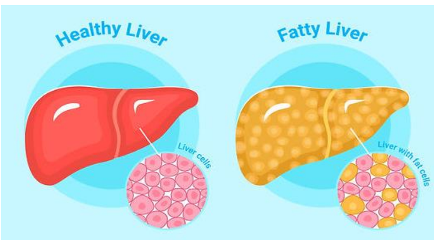

Fig. 1. Fatty Liver Disease

II. LITERATURE REVIEW

Number of obstacles impede the precise forecasting of FLD, such as:

Variability in the signs and course of FLD:

The wide range of presentations and results seen in those afflicted with FLD is referred to as the heterogeneity of FLD symptoms and development [1]. Full-Thickness Liver Disease (FTLD) includes a variety of liver conditions, such as

Hepato Cellular Carcinoma (HCC), Cirrhosis, Fibrosis, and Non-Alcoholic Steato Hepatitis (NASH) as well as simple steatosis (fat build up in liver cells).

This diversity shows up in the following number of ways:

(1). Histological Variability:
There is a great deal of variation in the liver histology of people with FLD. There are different levels of fat accumulation associated with simple steatosis, from mild to severe. Histological findings of NASH range from moderate inflammation to severe fibrosis and cirrhosis [2]. The condition is characterized by inflammation, hepatocyte damage, and fibrosis.

(2). Clinical Presentation:
There is considerable variation in how FLD presents clinically. As for the problems associated with FLD, some people may experience hepatomegaly, jaundice, ascites, or hepatic encephalopathy, while others may stay asymptomatic or have vague symptoms like weariness and abdominal discomfort [3].

(3). Progression Rate:
The pace at which FLD progresses varies from person to person and can be influenced by a variety of factors, such as genetic susceptibility, dietary and exercise habits, comorbid illnesses (such diabetes and obesity), and environmental exposures (such as alcohol use) [4].

(4). Reaction to Treatment:
For FLD, there can be a wide range of reactions to therapy measures. Although first-line treatments for FLD include lifestyle modifications (e.g., diet adjustments, exercise), the efficacy of these interventions varies throughout patients [5].

(5). Hazard of Complications:
Patients with FLD have differing risks of experiencing cirrhosis, hepatocellular cancer, and liver fibrosis. While some FLD patients may suffer a relapse of liver fibrosis with proper treatment, others may remain relatively stable or progress to late stages of liver disease and perhaps die as a result [6].

Accurate diagnosis, risk assessment, and individualized treatment plans depend on an understanding of the variability of FLD signs and progression [7]. In order to maximize patient outcomes and stop the disease from progressing, clinicians must consider the distinct qualities of every patient, the seriousness of the illness, and risk factors when assessing and managing FLD [8].

A. Restricted access to excellently labelled datasets:
One major obstacle to the field of FLD study is the scarcity of high-quality labelled datasets. Training and assessing Machine Learning (ML) models for FLD prediction, risk assessment, and therapy monitoring require labelled datasets [9].

(1). Data Privacy and restrictions:
Sensitive medical data is subject to stringent privacy restrictions (e.g., HIPAA in the United States GDPR in the European Union), including imaging investigations (e.g., MRI, ultrasound), clinical records and biochemical indicators. Labelled medical datasets are difficult to access and share while adhering to privacy restrictions, which limits their availability for study [10].

(2). Data Annotation and Collection Costs:
Funding, manpower, and infrastructure are only a few of the major resources needed to gather excellent labelled datasets for FLD research [11].

(3). Heterogeneity of FLD:
A variety of disorders with varying etiologies, symptoms, and clinical trajectories are included in the umbrella term "fatty liver disease" [12]. It can be difficult to create labelled datasets that sufficiently ensure representativeness and sample size while capturing this variation. The process of creating a dataset is further complicated by variations in imaging techniques, disease severity, and patient demographics [13].

(4). The availability of longitudinal data:
Longitudinal data is important for understanding the natural history of FLD and assessing the efficacy of therapies [14]. It follows the course of the disease and the results of treatment over time. However, gathering longitudinal datasets with meticulously annotated follow-up data presents practical difficulties and can necessitate cooperation across several healthcare facilities [15].

(5). Limited Publicly Available Datasets:
Despite the fact that there are some publicly available datasets for FLD research (such as the NAFLD Database, UK Bio bank, and NHANES), these datasets may be limited by factors including a small sample size, insufficient clinical data, or a lack of histological confirmation of FLD diagnosis [16].

- Promoting partnerships and data sharing programs amongst academic institutions to make a variety of well-annotated datasets more accessible [17].

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- Creating defined procedures to guarantee uniformity and interoperability amongst studies for data gathering, annotation, and exchange.
- Enhancing current datasets and addressing sample size constraints by utilizing cutting-edge data augmentation techniques and synthetic data production approaches [18].
- Investigating possibilities for distributed data analysis and federated learning to support cooperative model training while maintaining data security and privacy.
- Investing money into the tools and infrastructure needed for data storage, annotation and curation in order to facilitate the production and distribution of massive datasets [19].
- Researchers can create more precise, reliable and broadly applicable machine learning models for disease diagnosis, prognosis and tailored treatment by tackling the problem of scarce dataset availability [20].

B. Unbalanced class distributions, having comparatively few FLD cases:

The creation and assessment of ML models for the prediction of FLD are significantly hampered by the unbalanced class distribution, wherein cases of FLD are comparatively infrequent in comparison to non-cases [21]. Predictive model performance and generalization may be impacted by a number of problems that arise from this imbalance in class distribution, including:

(1). Bias towards Majority Class:

Machine learning models that have been trained on unbalanced datasets have a tendency to give the majority class (non-FLD cases), priority over the minority class(FLD cases) [22].

(2). Learning Minority Class Patterns is Difficult:

ML algorithms find it difficult to learn and generalize from the patterns associated with the minority class because there are a few FLD cases in the dataset [23]. The model may perform less well in FLD prediction if it has trouble recognizing minute traits or attributes that set FLD instances apart from Non-FLD cases.

(3). Model Evaluation Biases:

Because traditional performance measurements don't take the class distribution into account, they can be deceptive when assessing imbalanced datasets. One example of this is accuracy. If models prioritize the majority class, they may attain high accuracy but still perform badly in identifying FLD situations [24]. When evaluating a model's performance on imbalanced datasets, evaluation metrics including Area Under the Curve - Receiver Operating Characteristic Curve (AUC-ROC), F1-score, recall, sensitivity, specificity and accuracy and F1-score are more useful [25].

(4). The possibility of over fitting to the majority class:

It exists in machine learning models that were trained on unbalanced datasets. This might lead to subpar generalization performance on new data. Instead of capturing the essential traits of both classes, the model might be trained to memorize patterns unique to the majority class.

C. *Handling Class Imbalance:*

- To obtain a more balanced dataset distribution, resampling approaches like under sampling the majority class (non-FLD situations) or oversampling the minority class (FLD cases) can be used.
- Techniques for creating synthetic examples of the minority class, such as SMOTE (Synthetic Minority Over-sampling Technique) data generating techniques.
- Methods for cost-sensitive learning that increase the penalties for incorrectly classifying members of the minority group during model training.

D. The intricacy of the biological systems that underlie FLD:

A major obstacle to comprehending the pathophysiology of FLD and creating reliable predictive models is the intricacy of the underlying molecular systems that contribute to the condition. A complex combination of genetic, environmental, metabolic and behavioural variables can contribute to FLD.

(1). FLD develops and progresses due to number of biological causes, including:

- Insulin Resistance and Metabolic Syndrome
- Activation of Inflammatory Pathways
- Oxidative Stress and Mitochondrial Dysfunction
- Genetic and Epigenetic Variants
- Gut-Liver Axis Dysfunction
- Environmental and Lifestyle Factors

(2). Clinical setting interpretability and explainability of Machine Learning Models:

- Risk Assessment and Stratification
- Treatment Planning and individualized Medicine
- Transparency and accountability

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(3). Several tactics can be used to improve the explainability and interpretability of machine learning models in clinical settings:

- Feature Importance Analysis
- Model Visualization
- Rule-Based Models
- Model Reporting and Documentation

III. MACHINE LEARNING TECHNIQUES

For FLD prediction, a variety of ML Techniques have been used, including:

A. Logistic Regression:

In binary classification problems, a statistical model known as logistic regression is utilized with the aim of estimating the probability that an observation falls into one of two groups that are mutually exclusive. Despite its name, logistic regression is a classification algorithm rather than a regression algorithm.

(1). The following are the main features of logistic regression:

- Model Representation
- Decision Boundary
- Loss Function
- Gradient Descent
- Regularization
- Interpretability
- Applications

B. Decision Trees:

(1). Main Features of Decision Trees:

- Tree Structure
- Decision Nodes
- Leaf Nodes
- Splitting Criteria
- Managing Numerical and Categorical Data
- Tree Depth

(2). Ensemble approaches:

Based on Decision Trees, techniques like Random Forests and Gradient Boosting are well-liked ensemble approaches that mix several trees to increase resilience and generalization.

(3). Applications:

Decision trees find use in many different fields, including customer relationship management (churn prediction), finance (credit scoring), healthcare (diagnostic), and more.

C. Random Forests:

A member of the ensemble learning method family, Random Forests are an extension of Decision Trees. The following are Random Forests salient features:

(1). Ensemble Method:

Decision Trees are gathered into an ensemble, or Random Forest. To increase accuracy and decrease over fitting, Random Forests construct many Decision Trees and aggregate their predictions, as opposed to depending solely on one.

(2). Random Sampling:

Forests employ a technique known as bootstrap aggregating, also referred to as bagging, to generate distinct training datasets through random sampling from the original dataset using replacement. Every tree receives training from a distinct bootstrap sample.

(3). Feature randomization:

Random Forests offer randomization to feature selection in addition to sampling data points (bootstrap sampling). Rather than considering all features, at every decision tree node, a random subset of features is considered for splitting. This improves generality and helps decorate the trees.

(4). Decision Aggregation:

Random Forests use majority voting to combine the predictions made by each individual tree in classification problems. The average of all trees predictions is used for regression tasks.

(5). Tree Diversity:
The goal of Random Forests is to produce trees with a variety of structures and forecasts. Unlike individual Decision Trees, this variety is attained via random sampling of characteristics and data, which lowers the chance of over fitting.
(6). Scalability:
High-dimensional feature spaces in huge datasets may be handled effectively by Random Forests. Multiple trees can be trained in simultaneously, which increases their scalability for large-scale data applications.
(7). Robustness:
Because forecasts are averaged over a number of trees, Random Forests are resistant to noise and anomalies in the data. They usually function well even without a lot of hyper parameter adjustment.
(8). Feature Importance:
Using Random Forests, one can determine the relative importance of features by figuring out how much each feature contributes to the total decrease in impurity (or increase in purity) among all trees. Knowing which features are most important for prediction can be aided by this.

D. Support Vector Machines (SVM):
Support vector machines (SVMs), supervised learning models, are used for regression and classification applications.
(1). The following are Support Vector Machines salient features:
- Linear and Non-linear Classification
- Margin Maximization
- Kernel Trick
- Support Vectors
- C-Support Vector Classification (C-SVC)
- Regression with Support Vector Regression (SVR)
- Kernel Selection
- Regularization

(2). Applications:
SVMs are applied in a variety of fields, including text categorization, image classification, bioinformatics and financial markets, for both regression and classification tasks where high accuracy and generalization are required.

E. Artificial Neural Networks (ANN):
Strong machine learning models called Artificial Neural Networks (ANNs) are modelled after the neural architecture of the human brain. The following are Artificial Neural Networks salient features:
(1) Neural Structure:
- Input Layer
- Hidden Layers
- Output Layer

(2). Deep Learning:
Deep Neural Networks (DNNs) are ANNs with several hidden layers. Deep learning achieves state-of-the-art performance in tasks like speech and image recognition by using DNNs to create hierarchical representations of input.
(3). Regularization:
To avoid over fitting in ANNs and improve generalization to unknown data, strategies like dropout and weight regularization (L1 and L2) are employed.
(4). Hyper parameters:
Important hyper parameters include the number of layers, the number of neurons in each layer, the activation function chosen, the learning rate, the batch size and the number of epochs. Achieving optimal performance requires optimizing certain hyper parameters.
(5). Challenges:
For training, ANNs need a lot of labelled data and a lot of processing power, especially for deep designs. It takes skill and patience to fine-tune the architecture and hyper parameters.
(6). Convolutional Neural Networks (CNN):
Convolutional neural networks (CNNs) are specialized deep learning models designed to analyze structured, grid-like data, like images. The main features of convolutional neural networks are as follows:
- Convolutional Layers
- Filters (Kernels)
- Feature Maps
- Pooling Layers
- Max Pooling
- Activation Functions
- Fully Connected Layers

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- Dense (Fully Connected) Layers Parameter Sharin
- Translation Invariance
- Transfer Learning

(7). Applications:
Object identification, picture segmentation, facial recognition, medical image analysis and autonomous driving are just a few of the image and video recognition tasks that CNNs are frequently utilized.
(8). Challenges:
Deep architecture training in particular demands a large amount of processing power from CNNs. Regularization strategies and data augmentation are necessary when there is over fitting due to either too little data or too much model complexity.
(9). Gradient Boosting Machines (GBM):
Fundamentals of Gradient Boosting Machines:

- Ensemble Learning
- Boosting
  - Gradient Descent
  - The Operation of GBM
  - Base Learner
  - Calculation of Residuals
  - Gradient Descent
  - Final Prediction

(10). Often Used Implementations:
XG Boost: Tianqi Chen's eXtreme Gradient Boosting is a popular solution renowned for its performance and scalability.
Light GBM: Microsoft created another effective solution that is geared toward speed and large datasets.
Cat Boost: Yandex created CatBoost, an efficient tool for handling categorical data that doesn't require a lot of pre-processing. Gradient Boosting because of their precision and adaptability, machines have gained popularity in a variety of machine learning contests and real-world applications. However, in order to avoid over fitting, parameters must be carefully adjusted.

F. Ensemble Learning Methods:
In machine learning, ensemble learning approaches integrate several independent models (sometimes referred to as base learners) to enhance prediction performance. The concept underlying ensemble approaches is that total forecast accuracy can be greatly improved over the use of a single model by integrating numerous models, each of which captures various parts of the data or makes distinct sorts of errors.
These are a few well-liked techniques for group learning:

- Bootstrap Aggregating, or Bagging
- Boosting
- Generalization Stacking (Stacking)

G. Random Forest:
Description: An ensemble learning method called Random Forest makes use of many decision trees and is based on bagging.

Goal: The aim of this technique is to control over-fitting and increase accuracy by averaging decision trees that were trained on distinct portions of the dataset.

IV. METHODOLOGIES

Research on FLD prediction uses a variety of approaches such as,

- Model Ensemble Methods
- Cross-Validation
- Feature Selection

V. PERFORMANCE EVALUATION METRICS

The following are typical metrics used to assess FLD prediction models:

F1-score, accuracy, sensitivity, specificity, Matthews Correlation Coefficient (MCC), Area Under the Precision-Recall Curve (AUC-PR), and Area Under the Receiver Operating Characteristic Curve (AUC-ROC).

VI. CONCLUSION

There are significant prospects available for improving prediction accuracy of fatty liver disease using machine learning approaches. Researchers can create reliable predictive models that support early detection, risk assessment, and individualized management plans for FLD patients by utilizing a variety of datasets and cutting-edge algorithms. For ML-based techniques to be successfully incorporated into clinical practice, it is still necessary to solve issues with data quality, model interpretability, and therapeutic value.

ACKNOWLEDGMENT

The authors sincerely acknowledge the scientists and medical experts whose knowledge and research in the domains of machine learning and fatty liver disease have made this study possible. Their ground breaking work will have further investigation enhancing prediction accuracy using Machine Learning techniques in identifying Fatty Liver Disease.

Wordbook:

FLD	-	Fatty Liver Disease
ML	-	Machine Learning
DNL	-	De Novo Lipogenesis
NASH	-	Non-Alcoholic Steato Hepatitis
FTLD	-	Full-Thickness Liver Disease Hepatitis
ROS	-	Reactive Oxygen Species
DNA	-	Deoxyribo Nucleic Acid
GWAS	-	Genome-Wide Association Study
RNA	-	Ribo Nucleic Acid
FDA	-	Food and Drug Administration
EMA	-	Exponential Moving Average
HCC	-	Hepato Cellular Carcinoma
TNF-α	-	Tumor Necrosis Factor-alpha
SMOTE	-	Synthetic Minority Over- Sampling Technique
NAFLD	-	Non-Alcoholic Fatty Liver Disease
RELU	-	Rectified Linear Unit
ANN	-	Artificial Neural Networks
SHAP	-	Shapley Additive exPlanations
NHANES	-	National Health and Nutrition Examination Survey
CNN	-	Convolutional Neural Network
RNN	-	Recurrent Neural Network
DNN	-	Deep Neural Networks
LIME	-	Local Interpretable Model- agnostic Explanations
SVC	-	Support Vector Classification
CCC	-	Cost Complexity Parameter
SVR	-	Support Vector Regression
VGG	-	Visual Geometry Group
GBM	-	Gradient Boosting Machines
AUC-PR	-	Area Under the Precision-Recall Curve
AUC-ROC	-	Area Under the Curve - Receiver Operating Characteristic Curve
MCC	-	Matthews Correlation Coefficient

REFERENCES

[1]. Shaban, Warda M, "Early diagnosis of liver disease using improved binary butterfly optimization and machine learning algorithms." *Multimedia Tools and Applications 83.10 (2024): 30867-30895.*

[2]. Cao, Tengrui, Qian Zhu, Chao Tong, Aheyeerke Halengbieke, Xuetong Ni, Jianmin Tang, Yumei Han, Qiang Li, and Xinghua Yang, "Establishment of a machine learning predictive model for non-alcoholic fatty liver disease: A longitudinal cohort study." *Nutrition, Metabolism and Cardiovascular Diseases 34, no. 6 (2024): 1456-1466.*

[3]. Li, Zhao, Lan Lan, Yujia Zhou, Ruoxing Li, Kenneth D. Chavin, Hua Xu, Liang Li, David JH Shih, and W. Jim Zheng, "Developing deep learning-based strategies to predict the risk of hepatocellular carcinoma among patients with nonalcoholic fatty liver disease from electronic health records." *Journal of Biomedical Informatics 152 (2024): 104626.*

[4]. Islam, Rakibul, Azrin Sultana, and Mohammad Rashedul Islam, "A comprehensive review for chronic disease prediction using machine learning algorithms." *Journal of Electrical Systems and Information Technology 11.1 (2024): 27.*

[5]. Inamdar, Safdar Wahid, and Abdulhamit Subasi, "Artificial intelligence–based fatty liver disease detection using ultrasound images." *Applications of Artificial Intelligence Healthcare and Biomedicine. Academic Press, 2024. 175-204.*

[6]. Gil-Rojas, Sergio, Miguel Suárez, Pablo Martínez-Blanco, Ana M. Torres, Natalia Martínez-García, Pilar Blasco, Miguel Torralba, and Jorge Mateo, "Prognostic Impact of Metabolic Syndrome and Steatotic Liver Disease in Hepatocellular Carcinoma Using Machine Learning Techniques." *Metabolites 14, no. 6 (2024): 305.*

[7]. Barrera, Francisco, Javier Uribe, Nixa Olvares, Paula Huerta, Daniel Cabrera, and Manuel Romero-Gómez, "The Janus of a disease: Diabetes and metabolic dysfunction-associated fatty liver disease." *Annals of Hepatology 29, no. 4 (2024).*

[8]. Huang, Peng, Shu Hu, Bo Peng, Jiashu Zhang, Xi Wu, and Xin Wang, "Robustly optimized deep feature decoupling network for fatty liver diseases detection." *In International Conference on Medical Image Computing and Computer-Assisted Intervention, pp. 68-78. Cham: Springer Nature Switzerland, 2024.*

[9]. Allenki, Jyoshna, and Hemant Kumar Soni, "Analysis of Chronic Liver Disease Detection by Using Machine Learning Techniques." *IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS), pp. 1-8. IEEE, 2024.*

[10]. Li, Zhao, Lan Lan, Yujia Zhou, Ruoxing Li, Kenneth D. Chavin, Hua Xu, Liang Li, David JH Shih, and W. Jim Zheng, "Developing deep learning-based strategies to predict the risk of hepatocellular carcinoma among patients with nonalcoholic fatty liver disease from electronic health records." *Journal of Biomedical Informatics 152 (2024).*

[11]. Martín-Saladich, Queralt, Juan M. Pericàs, Andreea Ciudin, Clara Ramirez-Serra, Manuel Escobar, Jesús Rivera-Esteban, Santiago Aguadé-Bruix, Miguel A. González Ballester, and José Raul Herance, "Metabolic-associated fatty liver voxel-based quantification on CT images using a contrast adapted automatic tool." *Medical Image Analysis 95 (2024).*

[12]. Pinheiro, Paulo S., Patricia D. Jones, Heidy Medina, Hannah M. Cranford, Tulay Koru-Sengul, Tim Bungum, Robert Wong, Erin N. Kobetz, and Katherine A. McGlynn, "Incidence of etiology-specific hepatocellular carcinoma: diverging trends and significant heterogeneity by race and ethnicity." *Clinical gastroenterology and hepatology 22, no. 3 (2024).*

[13]. Xie, Siyuan, Delong Chen, Yangke Cai, Liyi Xu, Oulan Liao, Xuan Jia, Xiaowei Ji, Hanwen Chen, Jianshan Mao, and Jianting Cai, "Evaluating the efficacy of GIPR agonists on non-alcoholic fatty liver disease: *A Mediation Mendelian Randomization Study." Digestive and Liver Disease (2024).*

[14]. Cao, Tengrui, Qian Zhu, Chao Tong, Aheyeerke Halengbieke, Xuetong Ni, Jianmin Tang, Yumei Han, Qiang Li, and Xinghua Yang, "Establishment of a machine learning predictive model for non-alcoholic fatty liver disease: A longitudinal cohort study." *Nutrition, Metabolism and Cardiovascular Diseases 34, no. 6 (2024).*

[15]. Nachit, Maxime, Marco Dioguardi Burgio, Anton Abyzov, Philippe Garteiser, Valérie Paradis, Valérie Vilgrain, Isabelle Leclercq, and Bernard E. Van Beers, "Hepatocellular carcinoma in patients with non-alcoholic fatty liver disease is associated with heterogeneous pattern of fat infiltration in skeletal muscles." *European Radiology 34, no. 3 (2024).*

[16]. Alizargar, Azadeh, Yang-Lang Chang, Mohammad Alkhaleefah, and Tan-Hsu Tan, "Precision Non-Alcoholic Fatty Liver Disease (NAFLD) Diagnosis: Leveraging Ensemble Machine Learning and Gender Insights for Cost-Effective Detection." *Journal of Bioengineering 11, no. 6 (2024).*

[17]. Reyes-Avendaño, Itayetzi, Ana Beatriz Villaseñor-Altamirano, Edilburga Reyes-Jimenez, Juan Manuel Velazquez-Enriquez, Rafael Baltiérrez-Hoyos, Carolina Piña-Vázquez, Pablo Muriel, Saul Villa-Treviño, Jaime Arellanes-Robledo, and Verónica Rocío Vásquez-Garzón, "Identification of key markers for the stages of nonalcoholic fatty liver disease: *An integrated bioinformatics analysis and experimental validation." Digestive and Liver Disease (2024).*

[18]. Li, Jinquan, Yi Zhang, Xiaohan Ma, Ruiqi Liu, Cuicui Xu, Qin He, and Ming Dong, "Identification and validation of cuproptosis-related genes for diagnosis and therapy in nonalcoholic fatty liver disease." *Molecular and Cellular Biochemistry (2024).*

[19]. Mathur, Siddharth, Priyansh Karodi, and Ritesh Dhanare, "Fatty Liver Disease Prediction Through Machine Learning." *International Conference on Sentiment Analysis and Deep Learning (ICSADL). IEEE, 2024.*

[20]. Allenki, Jyoshna, and Hemant Kumar Soni, "Analysis of Chronic Liver Disease Detection by Using Machine Learning Techniques." *International Students' Conference on Electrical, Electronics and Computer Science (SCEECS). IEEE, 2024.*

[21]. Mohamed, Marghny H., Botheina H. Ali, Ahmed I. Taloba, Ahmad O. Aseeri, Mohamed Abd Elaziz, Shaker El-sappgah, and Nora El-Rashidy, "Towards an Accurate Liver Disease Prediction Based on Two-level Ensemble Stacking Model." *IEEE Access (2024).*

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A Peer-reviewed journal
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DOI 10.17148/IMRJR.2025.020905

[22]. Hailat, H., Mustafa, A. M., Najadat, H., Alomari, M., & Freihat, S, “Addressing the Imbalanced Class Distribution in Fatty Liver Detection in CT Images Using Transfer Learning.”, *International Conference on Information and Communication Systems (ICICS) (pp. 1-6). IEEE, (2024).*

[23]. Islam, Rakibul, Azrin Sultana, and MD Nuruzzaman Tuhin, "A comparative analysis of machine learning algorithms with tree-structured parzen estimator for liver disease prediction." *Journal of Healthcare Analytics 6: 100358, (2024).*

[24]. Allenki, Jyoshna, and Hemant Kumar Soni, "Analysis of Chronic Liver Disease Detection by Using Machine Learning Techniques." *International Students' Conference on Electrical, Electronics and Computer Science (SCEECS), 2024.*

[25]. Alizargar, Azadeh, Yang-Lang Chang, Mohammad Alkhaleefah, and Tan-Hsu Tan, "Precision Non-Alcoholic Fatty Liver Disease (NAFLD) Diagnosis: Leveraging Ensemble Machine Learning and Gender Insights for Cost-Effective Detection." *Journal of Bioengineering 11:6, 600(2024).*