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OVERVIEW OF LIVER FIBROSIS DETECTION METHOD USING MACHINE LEARNING APPROACHES

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ABSTRACT

Liver fibrosis is a chronic illness that results from chronic liver diseases such as hepatitis, cirrhosis, haemochromatosis, and Non-alcoholic Fatty Liver Disease (NAFLD). For timely detection and improved patient outcomes, liver fibrosis must be accurately staged for effective patient management and treatment. Traditional diagnostic methods such as liver biopsies, have risks and are invasive, among other downsides. However, recent advances in Machine Learning (ML) have offered substitutes to detect liver fibrosis. ML approaches are emerging as effective tools for the non-invasive detection of liver fibrosis; they have the potential to increase detection accuracy and reduce the demand for invasive liver biopsies. This overview provides a summary of methods for detecting liver fibrosis, with a particular emphasis on ML and both traditional and contemporary assessment methods. In recent years, many machine learning algorithms have been used to predict liver fibrosis detection for the Genetic Algorithm (GA), Artificial Neural Network (ANN), Naïve Bayes, and Multi-linear Regression, as well as Random Forest, Genetic techniques, Decision Tree (DT), Support Vector Machine (SVM), and Particle Swarm Optimisation (PSO). Besides, the results and performance of ML approaches are reviewed with a comparison of existing research studies, which were used for the detection of liver fibrosis. This review provides a roadmap that will assist researchers in making the most of the extensive capabilities of machine learning algorithms to build secure predictive models.

2020 Mathematics Subject Classification:

Introduction

The liver is a vital organ in the body, responsible for supporting immunity, digestion, detoxification, metabolism, and vitamin storage. The contributing factors of liver disease include genetic anomalies, [1] excessive alcohol and drug use, fatty liver, cirrhosis, liver fibrosis, hepatitis infection, and toxic and drug use. Furthermore, these factors may contribute to the Hepatitis B and C viruses, which can cause liver fibrosis. Fibrosis may occasionally be reversible. Depending on how severe it is, liver scarring can take many forms. The death and survival rates related to liver fibrosis may differ significantly depending on early detection, proper diagnosis, and an adequate therapeutic response. Although it can be challenging and time-consuming, medical professionals have long relied on clinical intuition to diagnose liver problems. Therefore, it is essential to precisely and promptly diagnose hepatic fibrosis in patients in order to quickly select the appropriate treatment option and achieve the desired results. The spectrum of fibrosis stages, as determined by the METAVIR score, ranges from F0 to F4, as shown in Figure 1.

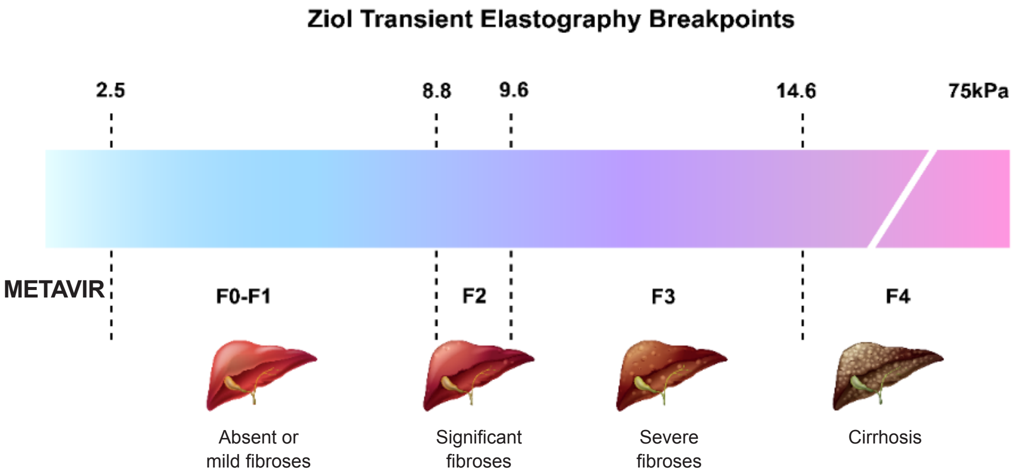

Figure 1: Stages of liver fibrosis [2]

Based on Figure 1, it can be seen that F0-F1 signifying no fibrosis, F1 to F2 signifying mild to moderate fibrosis, and F3 to F4 signifying severe fibrosis. The final stage of liver cirrhosis is F4. It is extremely difficult for many medical expert systems to diagnose the early stages of liver illness. Even when liver tissue has only been mildly injured. To classify the stages of liver fibrosis, many researchers [2, 3, 4, 5] have employed non-invasive imaging methods to assess the level of liver fibrosis, including Transient Elastography (TE) and vibratory waves. To the best of our knowledge, a comprehensive survey on HCV liver fibrosis detection has yet to be made. In this review article, we have discussed the liver fibrosis assessments with traditional and advanced methods, machine learning approaches, potential integration issues, and future directions.

Liver Fibrosis Assessment

The detection of liver fibrosis has encountered an important evolution across time from traditional invasive methods to modern non-invasive ones [6, 7]. This ground-breaking modification reflects the medical profession's continual search for valid and patient-friendly fibrosis assessment techniques. Conventional invasive methods are hindered by their intrusiveness and potential outcomes despite being successful. On the other hand, elastography and serum biomarkers [8] give patients instantaneous knowledge about the level of fibrosis without the side effects of invasive procedures.

Traditional Methods of Liver Fibrosis

The key to diagnosing and staging this chronic liver illness has always been the application of accepted techniques for evaluating hepatic fibrosis. Furthermore, the invasiveness of liver biopsy [9] and associated hazards have motivated current research initiatives attempting to enhance and make it safer. Table 1 demonstrates that there is certainly a need for new diagnostic procedures because traditional methods for assessing liver fibrosis have limitations. However, the liver biopsy [9], for instance, entails a risk of complications and may not adequately depict the variety of fibrosis over the entire liver. In contrast, blood indicators lack the necessary specificity and sensitivity despite being non-invasive, which could lead to an inaccurate diagnosis.

Table 1: Traditional methods of liver fibrosis assessment

Traditional Methods	Limitations
Liver biopsy [9]	Type of invasive procedure that creates potential complications like bleeding and infection. Additionally, sampling variability cannot adequately reflect the liver's condition through small tissue samples.
Blood makers [10]	Unable to determine whether or not a specific medical disease is present because they are neither sensitive nor specific due to numerous variables, including food, medications, and underlying medical conditions.
Ultrasound electrography [11]	It is an operator-dependent method and provides inaccurate results in obese patients due to the challenges.

Advanced Methods of Liver Fibrosis

In recent years [22-28], advanced methods for assessing liver fibrosis have arisen due to the limitations and drawbacks inherent with traditional methods, as illustrated in Table 1. Notably, modern methods offer a less invasive, more patient-friendly option and improve the overall risk profile associated with liver fibrosis detection. State-of-the-art methods such as serum biomarkers, magnetic resonance elastography, and transient elastography are remarkable courses of action due to their unique results of accuracy in liver fibrosis assessments. In Table 2, we present a comprehensive analysis of advanced methods for liver fibrosis assessment, highlighting key advantages.

Table 2: Advanced methods of liver fibrosis assessment

Advanced Methods	Key Advantages
Elastography	It provides real-time, quantitative information on tissue stiffness, which assists with the early detection of illnesses and reduces the need for invasive therapies.
Imaging modalities[12]	With MRIs (Magnetic Resonance Imaging), soft tissue in the non-ionising region can be examined with excellent clarity.
Machine learning [13]	Automates job and decision-making processes, scales to process large datasets efficiently, extrapolates enlightening findings from data and detects liver fibrosis.

Machine Learning Algorithms

The suggested methods [14-19] have employed a variety of strategies that allow machine learning algorithms to adapt the different computational parameters for liver fibrosis assessments successfully. In addition, based on clinical factors from blood tests, it is possible to predict and distinguish between various stages of liver fibrosis. Machine Learning (ML) approaches are as follows:

(a) Naïve Bayesian [20]: Probabilistic classifier which asserts that the likelihood of one occurrence given the possibility of another event really occurring is the foundation for its prediction.

(b) Decision Trees [21]: It creates classification models that resemble trees. It divides a dataset into more manageable chunks while also gradually growing a corresponding decision tree. The final tree is composed of decision nodes and leaf nodes. A decision node has two or more branches. A leaf node offers a selection. The objective is to create a model that forecasts the value of the target variable using a large number of input variables.

(c) Support Vector Machine (SVM) [22]: The SVM uses the best judgment boundary or line to categorise n-dimensional space. Both linear and non-linear SVMs are available. Contrary to non-linear SVMs, linear SVMs support the classification of data in a straight line. To ascertain the value of an attribute that is sorted based on the square of the weight supplied by the SVM.

(d) Principal Component Analysis (PCA) [23]: A statistical method that selects the primary features that best capture the dataset to decrease the number of dimensions in high-dimensional data.

(e) Artificial Neural Network (ANN) [24]: The value of the target variable is determined using a variety of input variables and produces categorisation models that look like trees.

(f) Random Forests [25]: One of the ensemble learning strategies for categorisation that is kept from being overfit.

(g) Extreme Gradient Boosting [28]: A type of gradient boosting technique that attempts to accurately predict a target variable by combining the predictions of a series of weaker and making the models simpler.

(h) Multiplayer Perceptron [27]: A multilayer perceptron consists of an input, an output, and one or more hidden layers, each of which has multiple neurons stacked on top of one another. In contrast to neurons in a perceptron, which must have an activation function that enforces a threshold.

Discussion on Existing Research Studies

In recent years, many researchers [7, 8, 28, 27] have conducted in-depth evaluations of the most recent improvements in the use of machine learning algorithms to diagnose liver fibrosis. This section thoroughly explores the several machine learning approaches, prominently highlights these initiatives. Based on the findings from existing studies, Figure 2 demonstrates that Random Forest is appropriate for predicting HCV and is utilised as a non-invasive tool to identify a disease's risk variables with 98.3% accuracy, as compared to the previous studies [24, 26-28]. In addition, the researcher states that ML approaches for liver fibrosis detection depend on the specific task, dataset characteristics, and desired performance metrics of accuracy.

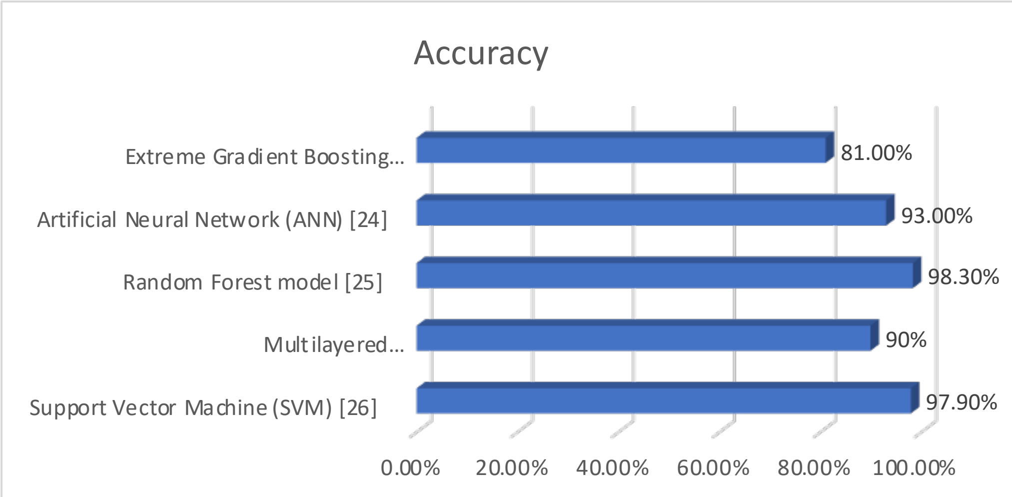

Figure 2: Accuracy of ML approaches

Conclusions

Liver fibrosis is caused by numerous viruses such as excessive alcohol and drug use, fatty liver, cirrhosis, hepatitis infection, and toxic and drug use. According to the METAVIR system, the liver fibrosis caused by this virus can range in severity from mild to moderate fibrosis to advanced fibrosis and cirrhosis. Some of these procedures, such as transient elastography, were developed based on liver imaging techniques, whereas others, like FIB-4 and APRI, were developed based on clinical symptoms. In this study, an overview of assessments of liver fibrosis is provided, which involves comprehending its foundational aspects such as the advanced and traditional methods and distinct stages of its progression.

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Conflict of Interest Statement

The authors declare there is no conflict of interest.

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