

Automatic Prediction of Non Alcoholic Liver disease Using Deep Learning Models

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Abstract - Fatty liver disease without alcohol consumption (NAFLD) is a universal, silent killer health issue without any proper, actual and effective treatment available worldwide. A prevalent and growing condition that causes a variety of colourful liver disorders is non-alcoholic fatty liver disease. It is rising quickly as a result of the increasing situations of hypertension, diabetes, and rotundity. These illnesses arise in cases where alcohol usage has no bearing on the liver damage. Since this can sometimes be fatal, there are a number of ways to identify it so that it can be treated quickly and recovered from. Thus, the applications of Deep Learning Convolutional Neural Network(CNN) techniques, which leverage the cases colourful natural qualities, is helpful in diagnosing and directly prognosticating cases of fatty liver disease without alcohol consumption.

It is a practical solution to these problems, and the authors have employed many parameters and features in this design to identify the complainants. This work suggests neural network-based techniques for the diagnosis of liver cancer. To extract features from an input image, a wavelet and a gray level co-occurrence matrix are utilized. This characteristic of the Gray level co-occurrence matrix divides the dataset into stages that are normal and aberrant. Several methods have been developed that use the size and shape of the abnormal lesion to detect liver tumours. This paper additionally proposes a unique methodology for the identification and diagnosis of liver tumours.

Keywords: *NAFLD, Pre-processing, Wavelet scattering transform, Grey level Co-occurrence matrix (GLCM) method and CNN.*

I. Introduction

Non-alcoholic fatty liver disease (NAFLD) [1, 2] has become to be a serious public health issue worldwide to an increasing extent. NAFLD is steadily increasing with an estimate of 20–30% prevalence rate. During the previous ten years, the prevalence rate of NAFLD [3] has increased two fold. Closely associated diseases with NAFLD are type 2 diabetes mellitus (T2DM) [4] which affects 60%-90%, hyperlipidaemia affects 27-92%, and other chronic illnesses affects 28–70% for people with obesity. As a result of NAFLD, liver fibrosis, liver cancer [5], tumours, liver steatohepatitis [6], liver cirrhosis and non-alcoholic steatohepatitis (NASH) [7, 8] all these diseases can occur. NAFLD is the main factor and for fast increase of liver cancer and now a day's non-alcoholic steatohepatitis (NASH) has become most common cause for liver failure.

As stated by large sample meta-analysis survey in 2014, 20.09% of grown up persons in main central China had NAFLD (9). In recent years China has seen a fast increase in the frequency of non-alcoholic fatty liver disease (NAFLD). As a consequence, it is critical and difficult to perform large-scale cohort research or study of causes of diseases on NAFLD. The execution of national physical examination motivates large-scale research; but a simple and fast approach is required for categorizing NAFLD patients in the general population.

Common NAFLD diagnostic methods [29] are ultrasound, Magnetic Resonance Imaging (MRI) and CT scan, but the costs of imaging tests are high. Histologic biopsy is the gold standard test for diagnosing non- alcoholic fatty liver disease (NAFLD).

However, when population screening is carried out widely, the cost of imaging testing is high. A numerous tests have been designed and fabricated for NAFLD diagnosis. The fatty liver index is an algorithm that foretells hepatitis steatosis for general population with the help of body weight, waist circumference or diameter, body mass index (BMI), serum triglyceride, and gamma glutamyl transferees (GGT) values (10, 11).

In order to calculate the percentage of liver fat content, the NAFLD liver fat score [12] algorithm takes into consideration the levels of the metabolic syndrome, type 2 diabetes, aspartate aminotransferase (AST), alanine aminotransferase (ALT), and fasting blood insulin. Age, gender, BMI, haptoglobin, total bilirubin, GGT levels, cholesterol, triglycerides, glucose, apolipoprotein A1 (ApoA1), A2-macroglobulin (A2M), and GGT levels are among the 12 predictive parameters in the SteatoTest logistic regression model [13].

White blood cell count, hypertension, triglycerides, high-density lipoprotein cholesterol, alanine aminotransferase, and hemoglobin A1c (HbA1c) are the six variables that make up a prediction model based on laboratory data.

However, there is a problem in obtaining these prediction parameters. Although the current NAFLD prediction models have been widely used, their application in many developing countries such as China and in large-scale epidemiological research remains confined/ limited.

Accurate prediction models have been developed with the help of machine learning. Machine learning models perform better and in an advanced manner when compared with traditional statistical approaches in terms of enhanced accuracy prediction, better modelling of complex relationships, enhanced capacity to gain knowledge from different data modules and solidly built to control data noise, machine learning mechanisms works better than traditional statistical techniques. These techniques have been used to diagnose fatty liver [14-16], meningitis [17], glaucoma [18], coronary heart disease [19], cancer, and other diseases [20, 21]. The main objective to use machine learning is to perform analysis of 304,145 physical examination subjects' data. Figure 1 shows the relationship between NAFLD with other diseases.

The impact of Artificial Intelligence, Machine Learning and deep learning in healthcare on many medical specialties has been the subject of numerous studies which includes pathology, radiology and clinical specialty.

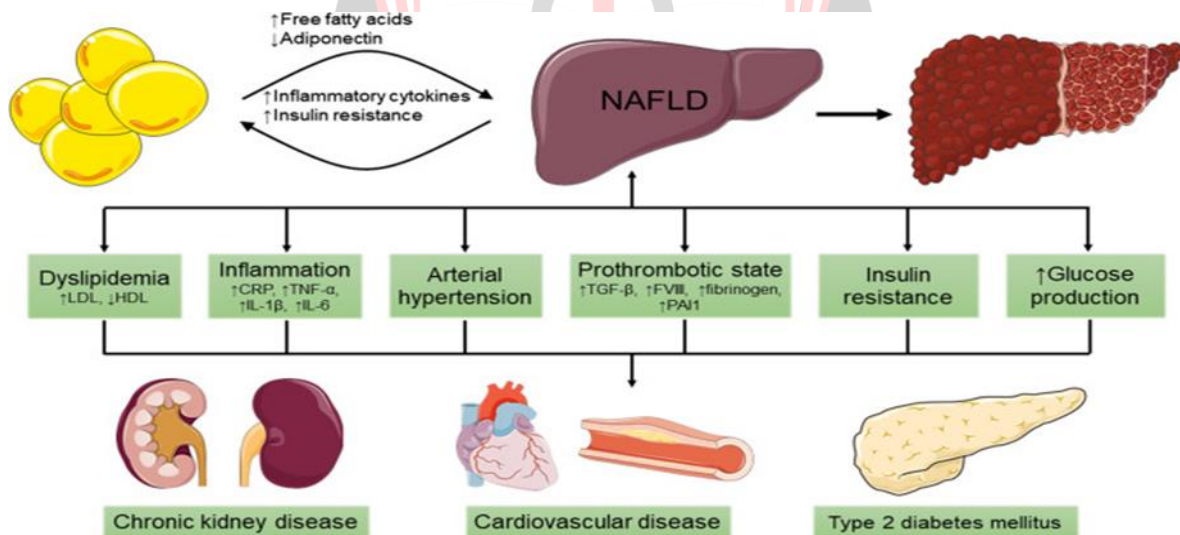


Figure 1. Association of NAFLD with various diseases

II. Related Work

The current study intends to address the probable bias and chances/opportunities for liver specialists doctors or pathologists provided by Artificial Intelligence, as well as also to provide a synthesised and thorough and extensive review of the applications and implementations of DNN algorithms related to liver pathology across the literature, in the field of study of tumour and also metabolism and inflammatory [22].

The following research were conducted in the last few years on the classification of fatty [23] and normal liver ultrasound pictures. This categorization process makes use of feature extraction and selection techniques [24].

By using LASSO regression, Weidong et al. [31] were able to reduce 17 indices to 12 indexes and obtain 12 non-zero coefficient features. Of the 304,135 individuals, 58,654 had NAFLD in total. The authors noted 17 different kinds of characteristics that were significantly ($p < 0.0001$) connected to NAFLD.

Garcia-Carretero et al. [32] has analysed and evaluated the generality of NASH in 2239 patients with hypertension and also the relevant characteristics linked to metabolic syndrome (MS) and hypertension [28] by the utilization of using supervised machine learning algorithms for example random forest classifier and least absolute shrinkage selection operator (LASSO). The random forest algorithm was used to evaluate the features in the LASSO regression pattern for significance. With single variable analysis, it was associated with metabolic syndrome, insulin resistance, type 2 diabetes [27] and dyslipidaemia. Serum ferritin and also insulin were successfully detected by the LASSO approach, under the curve of 0.79 area, with a sensitivity of 70%, and accuracy of 79% [32].

Many methods have been used, including bootstrap aggregating (bagging), random forest, k-nearest neighbor (kNN), decision trees, naive Bayes, support vector machines (SVM), adaptive boosting (AdaBoost), and k-nearest neighbor (kNN). Furthermore, and further employed the K2 algorithm [33]. Hidden naive Bayes (HNB) and aggregating one-dependence estimators (AODE) were added to the method. In an effort to determine the most accurate diagnosis model for NAFLD, Ma H et al. [33] investigated these 11 machine learning methods on 10508 individuals. The SVM model was shown to have the highest specificity and precision, with values of 0.946 and 0.725, respectively, whereas the logistic regression (LR) model had an accuracy of 83.41%. With a score of 0.680, the AODE model [33] was the most sensitive.

In order to compare logistic regression, AdaBoost, and ridge regression, Yip et al. gathered 922 samples. In the end, the logistic regression model produced six important traits, including triglycerides, insulin resistance, and alanine aminotransferase [34], with an accuracy of 87-88%.

The Support Vector Machine Classifier, Naive Bayes Classifier, K-Nearest Neighbors Classifier, Neural Network Classifier, Random Forest Classifier, Regularized Multinomial Classifier (using Logistic Regression), and Boosting Tree Classifier (using the Adaboost Classifier) were among the eight different machine learning algorithms that Sorino et al. [35] compared. Three models were developed using meta-learning techniques: the abdominal volume index plus GLUCOSE plus gamma-glutamyl trans peptidase plus SEX plus AGE, the body roundness index plus GLUCOSE plus GGT plus SEX plus AGE, and the FLI plus GLUCOSE plus SEX plus AGE.

The SVM algorithm, or support vector machine in Python, is said by the authors to be the most suitable and effective approach in the models they examined [35]. Compared to models 2 and 1, which were both 68% accurate, model 3's accuracy was 77%. It was believed that Model 2 [35] was the best model because it had less prediction errors.

In order to create a machine learning (ML) model to predict NASH, Docherty et al. [36] used data from the National Institute of Diabetes and Digestive and Kidney Diseases (NIDDK) dataset [30], which includes both verified NASH and non-NASH based on liver histology results.

The extreme gradient boosting model (XGBoost) shown remarkable performance in predicting NASH, as indicated by its area under the curve (0.82), sensitivity (81%), and accuracy (81%), based on 14 features [36]. In an incomplete feature set of five variables (0.79, 80%, and 80%, respectively) resulted in somewhat worse performance [36]. The whole model performed well (AUC 0.76), correctly predicting NASH in the best data. [36]. Using liver biopsy results to identify NASH and non-NASH patients, the authors' proposed NASH map model [36] was created and validated on a sizable real-world patient dataset.

Biswas et al. suggested a CNN-based network with unique layers of convolution, pooling, and inception to assess liver texture and determine a person's likelihood of developing fatty liver hepatitis within a certain symptomatic class. After removing any background data and retrieving the features of the ROI, this technique provides this region based on a gold truth. This strategy is restricted to organs where gold truth is established. As with previous methods [38], this makes it very evident that an expertise is required.

III. Methodology

Figure 2 depicts the architecture of the proposed methodology, which shows the various steps used in the methodology.

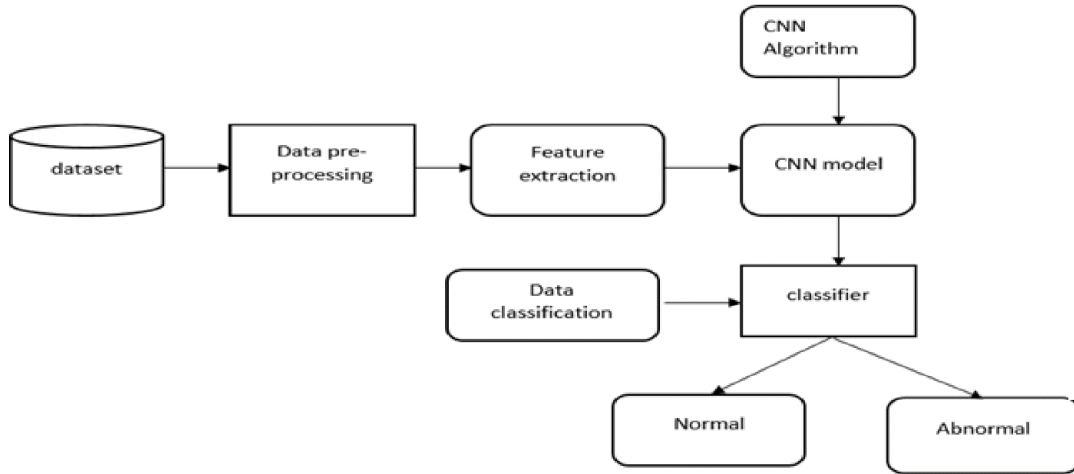


Figure 2. Architecture and work flow of the proposed methodology

3.1 Pre-Processing of data

Extensive and large amount of data is available, but it is disorganized and has a lot of missing values and outliers in its variables. As such, a critical first step is data preparation (25). Almost 200 factors that were unrelated to the study were first removed. Second, Pre-processing of data eliminates outliers and nulls. In order to do this, variables with more than 20% nulls were removed, while variables without any nulls were assigned. Furthermore, the mean was utilized to fill continuous variables and the mode was used to complete or fill categorical data.

$$\text{Min } w \quad 1/2n \quad || Xw-y ||^2 + \alpha \quad || w ||_1$$

The above figure shows equation (1)

Where 'w' means regression model's coefficient vector,

'n' represents number of samples,

'X' is a matrix of subject characteristics and

'||w||₁' is LASSO penalty with the constant value and the l1-norm of the coefficient vector ||w||₁ (26).

3.2 Processing of unbalanced data

There were more normal participants than NAFLD (an unbalanced-class issue) individuals. People with few courses typically find forecasting more challenging than those with many domains. The embedding method's penalized SVM algorithm was used to mitigate the negative effects of class imbalance. The basic idea behind the method is to increase the cost of categorization errors in the minority class.

The class_weight = 'balanced' option can be used to penalize minority errors during training by a proportion that corresponds to the minority's underrepresentation.

3.3 Feature Extraction

Feature extraction is the process to convert unprocessed data to more manageable numerical features while preserving the information included in the original data collection. It yields better results than applying machine learning directly on the raw data. In this work, main two feature extraction techniques used are Grey Co-occurrence Matrix and Wavelet Scattering.

3.3.1 Wavelet Scattering transform technique for feature extraction

Deep learning and machine learning applications can more easily extract low-variance information from images and data thanks to wavelet scattering networks. With the help of scattering networks, it may automatically identify attributes that minimize differences within a class.

Wavelet scattering transform is applied to data in stages. Figure 3 shows Wavelet scattering coefficient modulus. The output of one stage is the initial input for the stage that comes after. There are three operations in every stage. The zeroth-order scattering

coefficients are found by simply averaging the input. To extract reliable characteristics that are stable to mild deformation, rotation- and deformation-invariant, this work uses a wavelet scattering technique. Age, gender, level of physical activity, smoking, BMI, waist circumference, nutritional status, and preference for salty and fried foods were among the parameters that were retrieved.

Wavelet scattering networks make it easier for deep learning and machine learning applications to extract low-variance information from pictures and data. It might automatically determine characteristics that reduce differences within a class with the aid of scattering networks.

Wavelet scattering transform is applied to data in stages. The wavelet scattering coefficient modulus is shown in Figure 3. The first input for the step that follows is the output of the previous stage. In each step, there are three operations. By merely averaging the input, the zeroth-order scattering coefficients can be determined. This work employs a wavelet scattering technique to extract robust characteristics that are rotation- and deformation-invariant, stable under mild deformation. The parameters extracted are age, gender, amount of exercise, smoking, BMI, waist size, state of nutrition, and fried and salty food preferences.

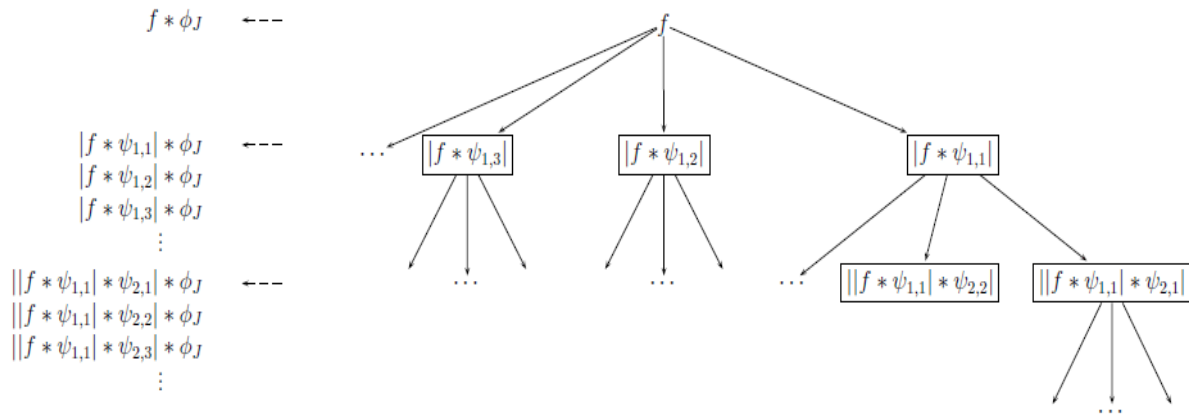


Figure 3. Wavelet scattering coefficient modulus

The wavelets are j , k , and f , and the scaling function is j . In the case of image data, there are several user-specified wavelet rotations for each j , k . A collection of edges that connects a root to a node is called an edge. Scalogram coefficients considered as the nodes of the tree. The scattering coefficients are obtained by convolving the scaling function 'J' with the Scalogram coefficients. The set of scattering coefficients are taken as low-variance characteristics which are derived from the data. Complexity with the scaling function, or low pass filtering, ends up in the loss of information. Nevertheless, in the next phase, while calculating the coefficients, the data is retrieved.

Before starting to extract features from the data set, design, generate and arrange/organize the whole network with the help of wavelet scattering (for data that is recorded over consistent time period) or waveletScattering2 (for photograph or graphical data). The amount of wavelets per octet in each and every filter bank, the total number of filter banks and the dimensions and proportions of the invariance scale can be controlled. Additionally, wavelet Scattering2 can be supplied with the number of wavelet rotations. To extricate the attributes from the data recorded consistently at regular intervals (time series data), feature matrix functions or wavelet scattering objects or scattering transform are used. To extricate the features from data image, waveletScattering2 object functions, feature Matrix, scattering Transform mechanisms are used.

The scattering transform produces the features iteratively, so scattering transform mechanism is used. The data is developed with the help of scaling function, f and J , before obtaining $S[0]$, which is the zeroth-order scattering coefficients. After that, do the following:

1. First of all, the wavelet transforming of the input data by using each and every wavelet filter in the first filter bank is determined.
2. Consider or include each and every filtered output's modulus. $U[1]$ which is the scalogram node representation.
3. Calculate the average of each modulus by using the scaling filter. $S[1]$ are considered as the values for the first-order scattering coefficients and which are the results.

Repeat the process at every node. The scattering and the scalogram coefficients are returned by the scattering transform function and the scattering characteristics are returned by the Matrix function.

3.3.2 Feature Extraction process by using Gray Co - occurrence Matrix

This well-liked technique for extracting texture features is based on statistical techniques. The probability of leaving a fixed position with gray level j and beginning at a pixel point with gray level i is expressed as this matrix. A matrix can be used to express all estimated values. The gray co - occurrence matrix used to extract features related to fatty liver is shown in Figure 4.

A point pair (x, y) is formed by all of the points in the image plus any points that deviate from it $(x+a, y+b)$. The gray value of these points combined is (i, j) . The values (i, j) are sorted into a square matrix after their frequency occurrences over the entire image are counted. The gray co - occurrence matrix is created by normalizing the total occurrence times to the probability of occurrence. Figure 4 displays the grey co - occurrence matrix used for feature extraction. Figure shows the healthy liver and fatty liver with the help of GLSZM, GLRLM and GLCM methods. GLSZM is gray level size zone matrix. GLRLM is a statistical method used in feature extraction process. It is a type of 2D histogram in the form of a matrix which records the occurrence of all various combinations of gray level values. GLCM measures the local variations in the image. It uses energy, correlation, contrast and homogeneity parameters.

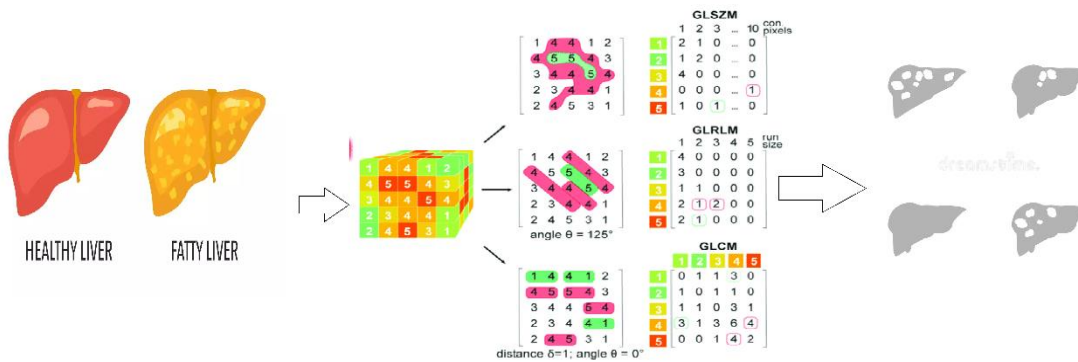


Figure 4. Grey Co - occurrence matrix implemented for feature extraction

3.4 Classification using CNN

CNNs are a type of Deep Neural Networks that are extensively used for visual image analysis. CNNs can identify and categorize specific aspects and elements in pictures. CNN uses and applications are image and video recognition, medical image and video analysis, picture classification, and natural language processing. CNN is helpful for picture recognition because of its great/high accuracy. Numerous businesses, including phone, security, recommendation systems, and medical picture analysis, use image recognition.

Figure 5 depicts the CNN architecture, which is made up of two main parts. A convolution tool that separates and identifies the image's many elements for analysis using a technique called "feature extraction," Many pairs of pooling or convolutional layers comprise the feature extraction network.

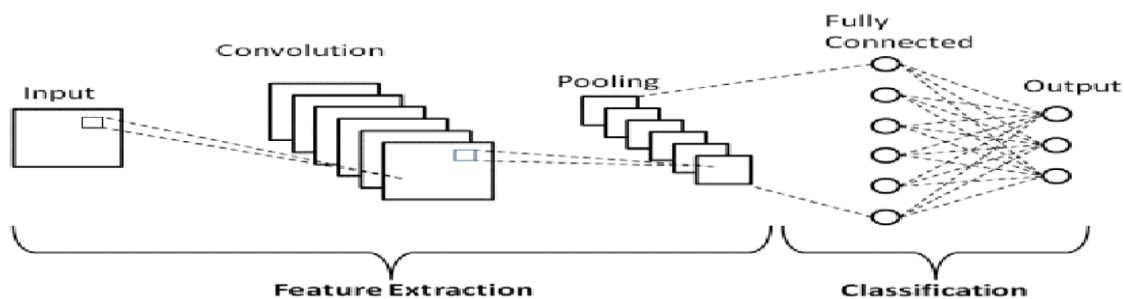


Figure 5. Architecture of CNN

A fully connected layer that utilizes the output of the convolution process and uses the previously extracted characteristics to anticipate the image class. Reducing the number of features in a dataset is the aim of this CNN feature extraction model. The pre-existing features from the original feature collection are summarized in the new features it creates. The many layers that comprise CNN are depicted in the architectural diagram. Examples of ultrasound images for patients with a) usual liver (Index 3%), and b) vulnerable livers (Index 20%) are shown in Figure 6 [38, 39].

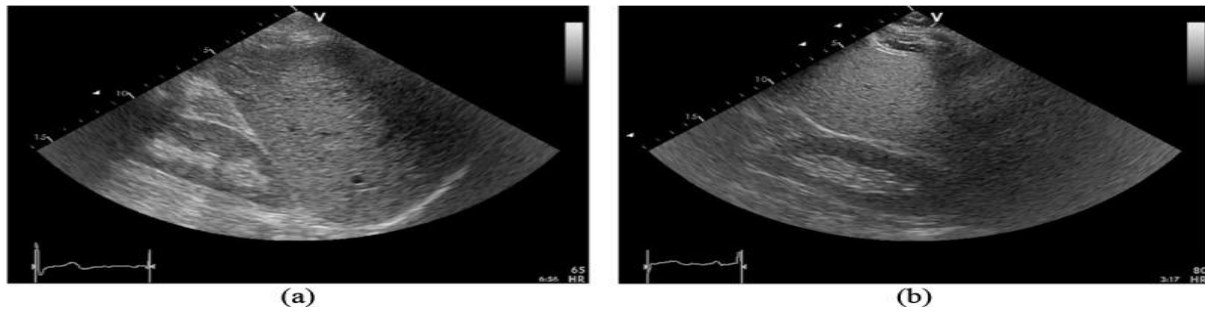


Figure 6. Image samples of ultrasound for patients: a) usual liver (Index 3%), b) Liver susceptible to fatty liver disease (Index 20%)

Different evaluation criteria are used in relevant networks for output accuracy. The three primary requirements are specificity, sensitivity, and accuracy.

Sensitivity is defined as the ratio of correctly classified items in class 1 (True Positive (TP)) to all components labelled in class 1 (True Positive (TP) + False Negative (FN)). The following formula is used to calculate the sensitivity:

$$\text{Sensitivity} = \frac{TP}{TP+FN} \tag{2}$$

Specificity: Specificity is also described by the percentage of elements categorized correctly in class 2 (True Negative (TN)), in comparison with all existing elements in class 2 (True Negative (TN) + False Positive (FP)), and it is represented in the following equation:

$$\text{Specificity} = \frac{TN}{TN+FP} \tag{3}$$

Accuracy: The accuracy indicator can be calculated as in the equation (4) and is described by the total number of elements correctly categorized to all presently used elements for classification.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{4}$$

For the states algorithm, sensitivity, accuracy and specificity criteria is computed. In general, confusion matrix will be helpful summary for expressing these attributes/parameters conditions for testing data so that the performances can be compared.

IV. Experimental Results

The CNN classification technique is applied to decide the performance of the work presented in this paper. These outcomes are offered for comparison with the pre-trained network methodology results from the related network. When CNN was used, the method proposed in this paper performed better than other models in terms of performance. Figure 7 shows the comparative study of models like XGBoost, random Forest, SVM, Bayesian network and ridge Regression with the proposed method. Sample Liver images are shown in figure 8. Table 1 represents comparison of primary data and real data with penalized SVM data samples. Table 2 shows the overall summary of the performance results for various networks along with the proposed technique in terms of accuracy, precision, recall, F1-score and AUC. The experimental results shows that the proposed method gives more accuracy in predicting non-alcoholic liver disease.

Dataset	Samples	Ratio	Description
Primary data	245,492/58,656	5:1	Primary/real data with all examples
Penalized SVM	243,302/243,302	1:1	Dataset balanced using penalized SVM

Table 1. Comparison of primary and real data with penalized SVM data samples

Network /Model	Accuracy	Precision	Recall	F1-Score	AUC
XG Boost	0.880	0.801	0.893	0.882	0.951
Random Forest	0.867	0.905	0.644	0.751	0.837
Bayesian Network	0.822	0.877	0.673	0.646	0.769
Ridge Regression	0.868	0.922	0.903	0.753	0.692
SVM	0.681	0.79	0.66	0.63	0.78
XGBoost	0.81	0.82	0.809	0.77	0.819
Proposed technique	0.882	0.923	0.895	0.888	0.952

Table 2. Summary of performance results for various networks

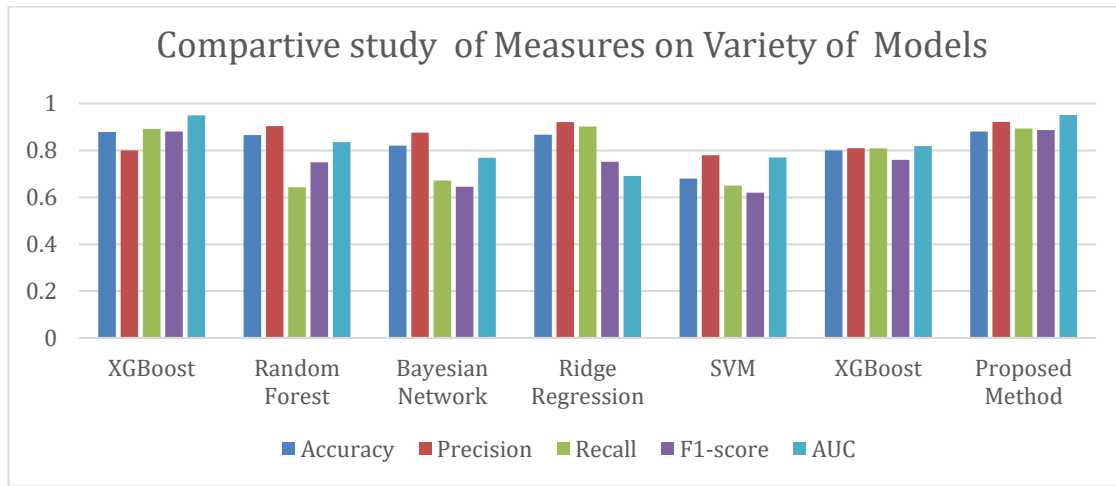


Figure 7. Comparative study of various models with the proposed model

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[[2939.9045]]
normal
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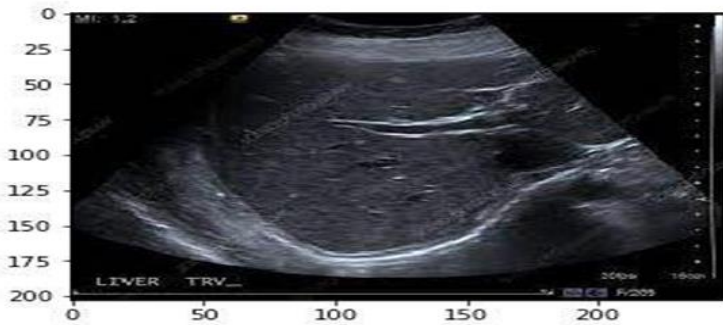


Figure 8. Normal Liver

Figure 8, which shows the image of a normal liver. Figure 9 shows the image of damage liver.


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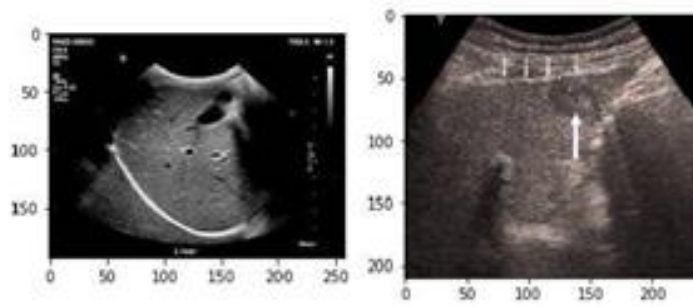


Figure 9. Sample damage liver image

V. Conclusion

An increasing amount of work has been done over time to more precisely identify and categorize fatty liver disease and the clinical stages that go along with it than can be done by hand. To finish the task, the majority of the work has been focused on feature extraction from processed photos. A big step in the right way is the use of CNN for classification in conjunction with a number of pre-processing and feature extraction methods.

More work needs to be put into developing problem-solving models and conducting randomized clinical trials on a larger patient population in order to further potential future research. Future attempts to create intelligible models will benefit from the insights. To identify the most correct phases of the photographs, further work must be done on photo processing and feature extraction while accounting for structural differences.

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