Machine Learning-based Segmentation to the Prediction of Liver Cirrhosis

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ABSTRACT
The liver is one of the most crucial organs in the human body. It performs several processes among them are metabolism, detoxification, bile formation, storage and blood-management, immunological function. Hepatitis, fatty liver disease, cirrhosis, and liver cancer are examples of the illnesses that can dangerously affect the liver. A liver transplant can be essential if the liver is seriously damaged or is not working properly. Liver function can be evaluated by diagnostic testing. The condition known as cirrhosis is a late stage of liver scarring (fibrosis) brought on by a variety of liver illnesses and disorders, including chronic hepatitis, alcoholism, fatty liver disease, autoimmune hepatitis, and a few genetic liver diseases. In addition to a physical examination, medical history, blood tests, imaging tests (such as an ultrasound, CT scan, or MRI), and occasionally a liver biopsy, cirrhosis is diagnosed. In this paper, a machine learning based model is used in order to detect, classify and predict the degree of cirrhosis based on previous regular laboratory tests only. Liver cirrhosis is classified into 3 classes: (F0-F1) for normal liver, (F2) for a moderate stage of liver cirrhosis, and (F3-F4) for complete liver cirrhosis. The algorithms used in this study are support vector machines, artificial neural networks, Gradient Boosting, K-Nearest Neighbor, and Naive Bayes. Results showed that, the Gradient Boosting algorithm achieved the best performance during both learning and testing phases with accuracy level of 86% during learning and 100% during testing.

General Terms
Cirrhosis, Liver, Liver diseases.

Keywords
Machine learning, Liver cirrhosis, liver laboratory tests.

1. INTRODUCTION
When the liver is harmed by some medications, alcohol consumption, hepatitis (A, B, C, D, and E), and fatty liver disease, its cells shift until they are ruined. Figure 1. illustrates liver disease. Liver cirrhosis, healthy fat, and Hepatocytes, or liver cells [2]

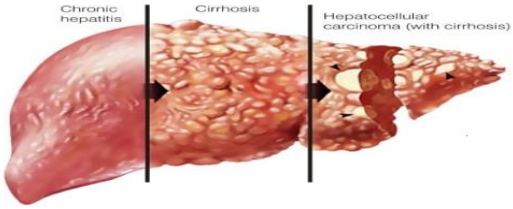

Fig. 1 Levels of liver cirrhosis

Numerous laboratory tests are available to evaluate the liver enzymes secreted into the circulation. Two enzymes that are sensitive indicators of liver damage are alanine aminotransferase (ALT) and aspartate aminotransferase (AST). A rise in volume of distribution causes a common reduction in albumin (ALB) in chronic liver diseases. The alanine transaminase (ALT) or SGPT enzyme is measured by this blood test. Chemicals called enzymes assist your body's cells in functioning. The liver produces the ALT enzyme. When tissues are harmed, it is released into the blood. [3]

A liver profile includes a blood test called the SGOT test. Serum glutamic-oxaloacetic transaminase, one of two liver enzymes, is measured. Aspartate aminotransferase is the name given to this enzyme in modern usage. The amount of liver enzyme in the blood is measured by an SGOT (or AST) test. The bilirubin test measures (Total bilirubin, "TB" and Direct bilirubin "DB"), the amount of bilirubin in your blood. It's used to help find the cause of health conditions like jaundice, anemia, and liver disease. Platelet test "PLT" improve liver fibrosis and accelerate liver regeneration. [4]

The Fibrosis-4 score is used to estimate cirrhosis. Cirrhosis has been estimated using four parameters (Age, SGOT, SGPT, and PLT)

Fibrosis-4 is estimated by [5]

$$FBI = \frac{Age \times AST}{PLT \times \sqrt[2]{ALT}} \quad \text{.....(1)}$$

Where:

Aspartate Aminotransferase (AST or SGOT) [U/L]
Alanine Aminotransferase (ALT or SGPT) $[U/L])^{1/2}$
Platelet Count (PLT) $[10^9/L]$.
Table1 represents the interpretation of FBI equation results. [6]

$$\textbf{Cirrihosis} \begin{cases} \textbf{FBI} \leq \textbf{1.54}, & \textbf{Normal} \\ \textbf{1.54} > \textbf{FBI} \leq \textbf{3.25}, & \textbf{Cirrhosis} \\ \textbf{FBI} \geq \textbf{3.26}, & \textbf{Complete Cirrhosis} \end{cases}$$

The next sections of the paper will be as follows: In Section 2, a survey of related works is presented. The proposed model is explained in Section 3, which includes dataset attribute analysis followed by the experimental results for each algorithm and comparison-based accuracy. Finally, the conclusion is presented in Section 4.

2. RELATED WORK
Tanwar et. al [7]**,** presented a model that reviews of the current state and expected developments in the use of machine learning to aid doctors or clinical experts in making timely, accurate decisions regarding the precise prediction and diagnosis of liver diseases.

Nasreen et. al [8] ,proposed a predictive model to aid doctors in the diagnosis of fatty liver disease and anticipate cases with high risk using machine learning techniques. The study made use of the abdominal ultrasound data from 577 patients at New

Taipei City Hospital. From these images, nine descriptors: systolic blood pressure, HDl-C, abdominal growth, diastolic blood pressure, glucose AC, SGOT-AST, triglyceride, and SGPT-ALT were extracted and provided to random forest (RF), artificial neural networks (ANNs), Naive Baye's (NB), and logistic regressions (LRs) machine learning classifier models, and the performance was validated with tenfold cross-validation with metrics AUC and accuracy. With an accuracy of 87.48% and an AUC of 0.925, the examination of the findings demonstrated the effectiveness of the random forest classifier.

Zhang [9]**,** 167 people without liver illness and 416 patients with liver disease from northeastern Andhra Pradesh, India, were the subjects of the analysis. This study develops a diagnosis model using total bilirubin and other clinical data as parameters based on patient age, gender, and other fundamental data. In this study, the diagnostic accuracy of two artificial intelligence techniques—random forest (RF) and support vector machine (SVM) models—was evaluated for patients with liver disease. The findings demonstrate the superior diagnostic accuracy of the support vector machine model based on the Gaussian kernel function, demonstrating the superiority of the SVM approach for the identification of liver disorders.

Sweidan et. al [10], proposed A fuzzy knowledge-based expert system for predicting the stage of liver fibrosis is known as a fuzzy fibrosis decision support (F2DS) system. It is based on a set of 17 symptoms and laboratory test findings, knowledge acquisition and machine learning algorithms, and domain expert knowledge. The system received a score of 95.7% on a variety of parameters used to evaluate it. It may be integrated into a healthcare system to help doctors and students pursuing medical degrees.

Alkhalifah et. al [11]**,** proposed a model for the purpose of diagnosing liver fibrosis (LF), a multilayer fuzzy expert system is created. Hunger, biliary status, ascites, age, and weariness are the input variables utilized in layer 1. Layer 2's input variables include the following: platelet count, white blood cell count, spleen, SGPT ALT, SGOT ALT, serum bilirubin, and serum albumin. The system has a classification accuracy of 95%, while its sensitivity, specificity, and precision are computed at 97.14%, 92%, and 94.44%, respectively.

Mazen [6] **,** uses an analytical hierarchy approach and the coefficient between its inputs to determine the weight of each fibrosis-4 input. The correlation coefficient model really demonstrated that there is a relationship between SGPT and SGOT but that there is none or very little between the other inputs. Then, using the Analytical Hierarchy Process, it was demonstrably shown that the most significant inputs that have an impact on fibrosis are SGOT with a weight value of approximately 53%, Age with a weight value of approximately 25%, PLT with a value of 16%, and SGPT with a weight value of approximately 5%.

Mazen [12] **,** A novel methodology for estimating the degree of cirrhosis utilizing the Multi-Layer Neural Network algorithm. Laboratory tests (including alanine aminotransferase (ALT), aspartate aminotransferase (AST), platelet count (PLT), total bilirubin (TB), direct bilirubin (DB), total proteins (TP), and albumin (ALB)) are used as inputs. FBI-4 findings for the same data were compared to the algorithmic outcome.

3. RESEARCH EXPERIEMENT

3.1.Problem statement

The liver's functioning can be harmed by overuse of medications, dietary supplements, alcohol, metabolic changes, viruses, and genetic anomalies, which can impact the liver and cause both infectious and noninfectious disorders. Hepatitis (viral infection), cirrhosis (liver scarring), fatty liver, cancer, Wilson's disease (abnormalities in metabolism), hemochromatosis (extra iron), and an acetaminophen overdose are a few of the conditions that can result in liver failure. Once the liver has developed complete cirrhosis, it stops functioning. Hepatic coma sets in as the liver patient's condition rapidly deteriorates. The classification of liver cirrhosis must thus be determined by doctors using costly and challenging biopsy analysis as well as Fibro-scan analysis.

3.2.Problem Solving phases

One of the most cutting-edge medical technologies today is machine learning, which makes it possible to forecast many diseases that were previously unable to be caught early on. This study examines the use of a variety of classification algorithms, including SVM, kNN, Naive Bayes, and Gradient Boosting, to classify liver cirrhosis. The model's correctness is determined by the testing phase, which also determines if a model is well-fitted, underfitted, or overfitted, as seen in Figure 2.

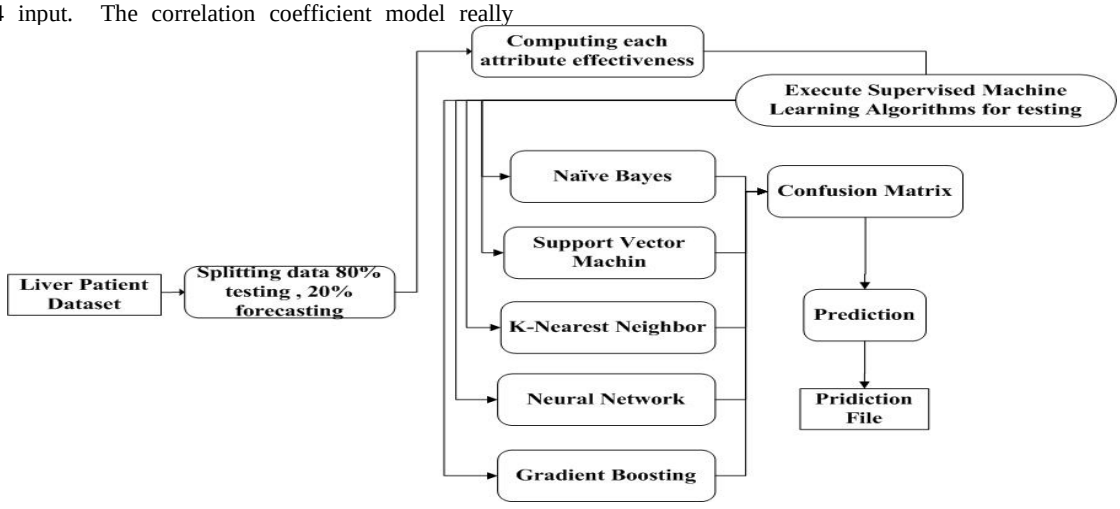

Fig. 2 Solving Problem Diagram

3.3.Dataset description

Authentic data sets are used in the study. The data that had been collected consisted of 730 Egyptian liver patients with 9 features. 20% of the dataset was utilized for testing, while 80% was used for training. The data set that had been used in the prediction consisted of 146 cases.

Dataset attributes are:

1. Age
2. Liver Laboratory tests
   A. Total Bilirubin "TB"
   B. Direct Bilirubin "DB"
   C. Alkaline Phosphate "Alkphos"
   D. SGPT
   E. SGOT
   F. ALB Albumin
   G. Platelet count "PLT"
3. Cirrhosis level

3.4. Define target

Liver cirrhosis level is provided into 3 classes (F0-F1, F2, and F3-F4) based FBI-4 equations that are represented in Section 1.

3.5.Dataset attributes ranking

The first step in the model is computing the dataset's attribute ranking. Dataset attributes are age, TB, DB, Alkphos, SGPT, SGOT, ALB Albumin, and PLT). Table 2 represents the ranking values.

As seen in Table 1. Based on the test, SGOT gains the highest importance, followed by PLT, DB, TB, SGPT, Alkphos, ALB, and age. In research [6], as illustrated above in Section 2, the researcher computes the effectiveness of each parameter in the FBI-4 equation. He proposed that SGOT is the highest, followed by age, PLT, and SGPT. However, when other parameters are added to this research, AGE comes at the end of the ranking.

Table 1. Ranking of dataset attributes

Features	Info. gain	Gain ratio	Gini	X^2
SGOT	21.5%	10.7%	8%	123.13
PLT	17.9%	9%	7.8%	99.19
DB	11.3%	5.9%	5%	41.67
TB	11.2%	5.6%	4.5%	52.31
SGPT	7.5%	3.8%	2.7%	44.51
Alkphos	6.5%	3.2%	2.4%	33.93
ALB	5.4%	2.7%	1.9%	33.16
Age	5.3%	2.6%	2.3%	32.44

3.6.Dataset attributes distribution with cirrhosis

Figures [3–8] show that lab data values with cirrhosis are skewed to the right. However, Figures [9, 10] represent lab data values for Age and ALB with cirrhosis that are supported by a normal distribution.

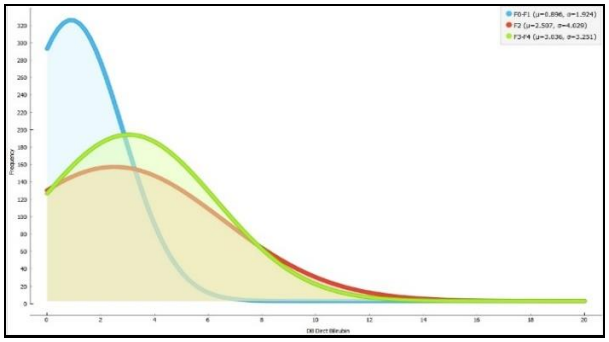

Fig. 3 Distribution of 'TB'

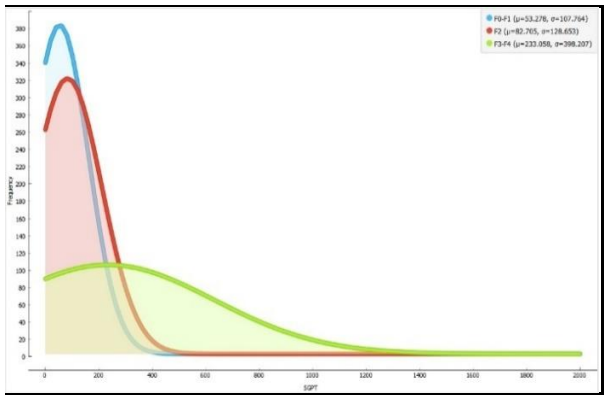

Fig. 4 Distribution of 'SGPT'

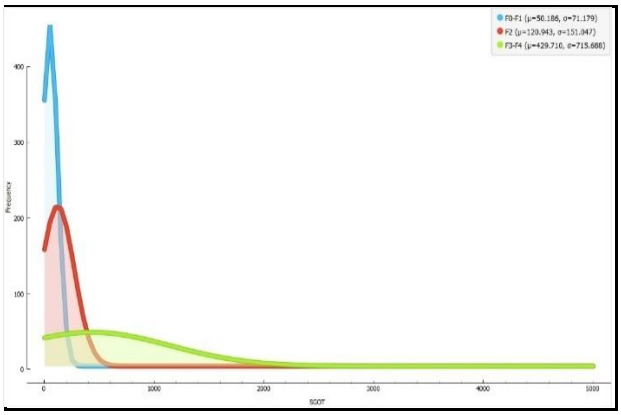

Fig. 5 Distribution of 'SGOT'

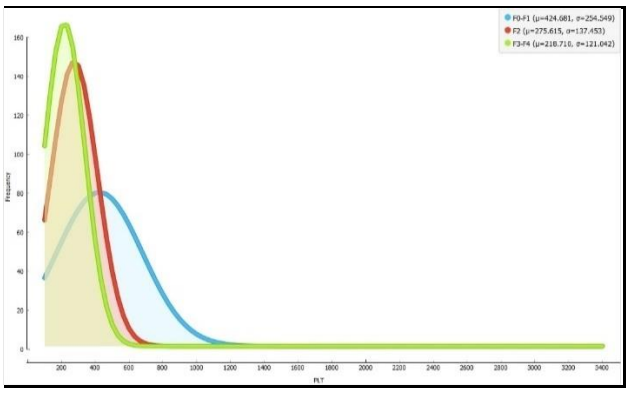

Fig. 6 Distribution of 'PLT'

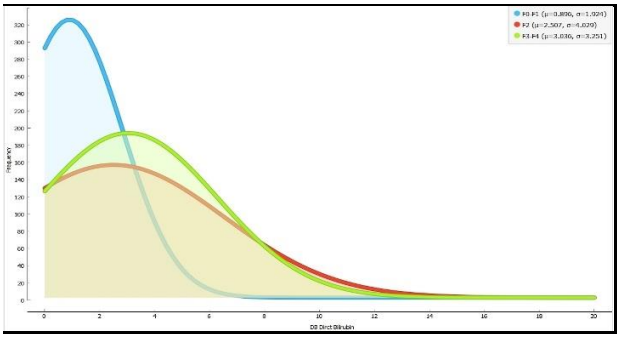

Fig. 7 Distribution of 'DB'

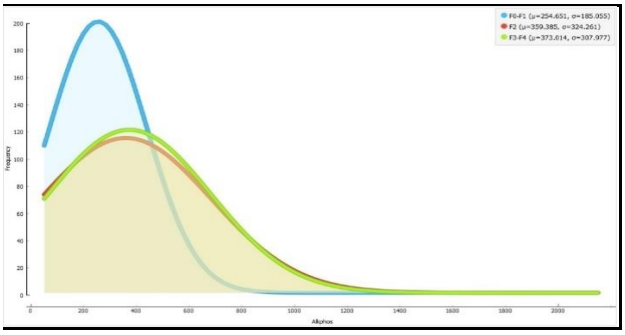

Fig. 8 Distribution of 'Alkphos'

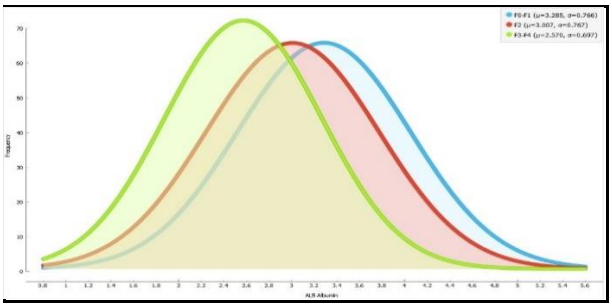

Fig. 9 Distribution of 'ALB Albumin'

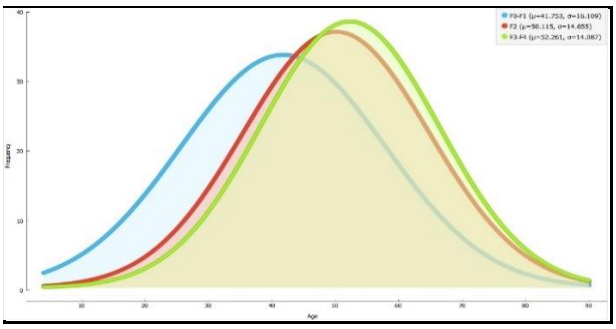

Fig. 10 Distribution of 'Age'

3.7.Executing Algorithms for learning dataset.

In this phase, as illustrated in the model diagram, supervised algorithms were executed. artificial neural networks

3.6.1 Artificial Neural Network "ANN"

As seen in Figure. 12, the neural network algorithm is represented. Laboratories' tests and patient age are represented in input layer neurons, and the output layer represents cirrhosis levels (F0-F1, F2, and F3-F4).

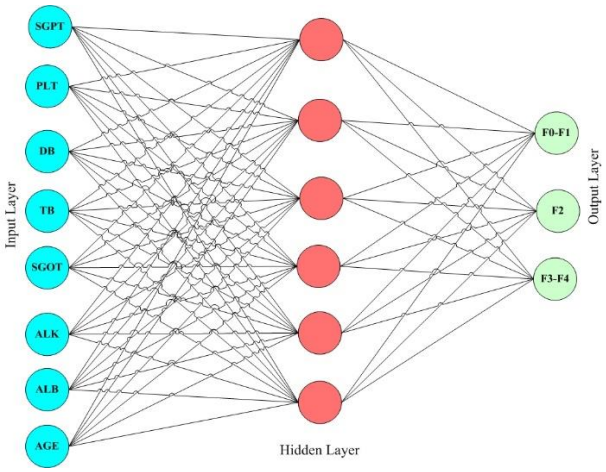

Fig. 11 ANN Algorithm

Table 2 Confusion matrix for the comparison between the actual and the predicted cirrhosis levels using ANN

		Predicted			
		F0-F1	**F2**	**F3-F4**	**∑**
Actual	**F0-F1**	379	13	0	**392**
	F2	51	50	21	**122**
	F3-F4	0	12	57	**69**
	∑	**430**	**75**	**78**	**583**

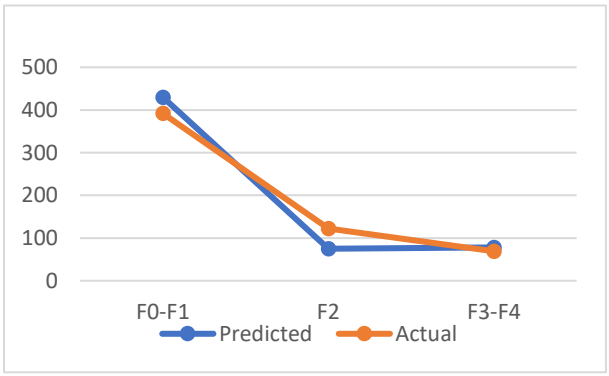

Fig. 12 Actual vs. Predicted using ANN

From the confusion matrix that is seen in Table 2 and Figure 12, 583 elements The actual elements for classes 1 (F0-F1), class 2 (F2) and class 3 (F3-F4) are 392, 122, and 69 respectively. However, the predicted elements were 430, 75, and 78.

- The precision for each class

$$\textbf{Precision} = \frac{\textbf{correctly predict}}{\textbf{total predict}} \quad \textbf{(1)}$$

Class 1 (F0-F1) = 379/430=88.1%.
Class 2 (F2) = 50/75 = 66.60%.
Class 3 (F3-F4) = 57/78=73.1%.

- The Recall for each class

$$\textbf{Recall} = \frac{\textbf{correctly predict}}{\textbf{Acutal}} \quad (2)$$

Class 1 (F0-F1) = 379/392=96.7%
Class 2 (F2) = 50/122=41%
Class 3 (F3-F4) = 57/69=82.6%

- The Accuracy for algorithm

$$\textbf{Accuracy} = \frac{\textbf{Total correctly predict}}{\textbf{Total Acutal}} \quad (3)$$

$$\text{Accuracy} = \frac{379 + 50 + 57}{583} = 83.4\%$$

- Weighted Average precision (WAP)

$$\textbf{WAP} = \sum_{i=0}^{n}\left(\frac{\textbf{Actual}}{\textbf{Total Actual}}\right)\textbf{Precision} \quad (4)$$

W*here*;
Actual is the correct results for each prediction,

$$\text{WAP} = \left(\frac{379}{583}\right)(88.1\%) + \left(\frac{50}{583}\right)(66.6\%) + \left(\frac{57}{583}\right)(73.1\%) = 0.572 + 0.057 + 0.071 = 0.701$$

3.6.2 *Support Vector Machine Algorithm*

From the confusion matrix that is seen in Table 3 and Figure 13, 583 elements The predicted elements were 453, 101, and 29.

Table 3 Confusion matrix for the comparison between the actual and the predicted cirrhosis levels using SVM

		Predicted			
		F0-F1	**F2**	**F3-F4**	∑
Actual	**F0-F1**	350	38	4	**392**
	F2	81	33	8	**122**
	F3-F4	22	30	17	**69**
	∑	**453**	**101**	**29**	**583**

- The precision for each class
  Class 1 (F0-F1) = 350/453=77.3%
  Class 2 (F2) = 33/101=32.7%
  Class 3 (F3-F4) = 17/29=58.6%

- The Recall for each class
  Class 1(F0-F1) = 350/392=89.3%
  Class 2(F2) = 33/122=27%
  Class 3(F3-F4) = 17/69=24.6%

- The Accuracy for algorithm

$$\text{Accuracy} = \frac{350 + 33 + 17}{583} = 68.6\%$$

- Weighted Average precision

$$\text{WAP} = \left(\frac{350}{583}\right)(89.3\%) + \left(\frac{33}{583}\right)(27\%) + \left(\frac{17}{583}\right)(24.6\%) = 0.463 + 0.018 + 0.017 = 0.499$$

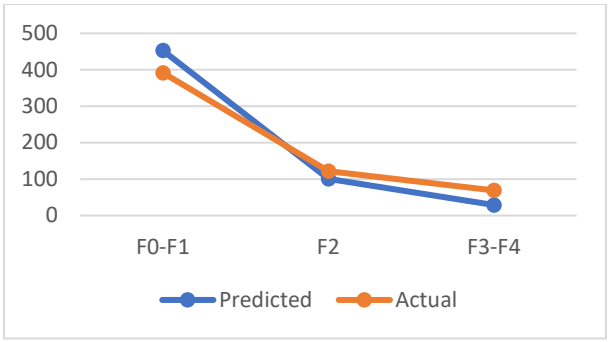

Fig. 13 Actual vs Predicted using SVM

3.6.3 *K-Nearest Neighbor*

From the confusion matrix that is seen in Table. 4 and Figure 14, from 583 elements. The predicted elements were 403, 119 and 61.

Table 4 Confusion matrix for the comparison between the actual and the predicted cirrhosis levels using KNN

		Predicted			
		F0-F1	**F2**	**F3-F4**	∑
Actual	**F0-F1**	359	30	3	**392**
	F2	43	59	20	**122**
	F3-F4	1	30	38	**69**
	∑	**403**	**119**	**61**	**583**

- The precision for each class
  Class 1 (F0-F1) = 359/403=89.1%
  Class 2 (F2) = 59/119=49.6%
  Class 3 (F3-F4) = 38/61=62.3%

- The Recall for each class
  Class 1(F0-F1) = 359/392=91.6%
  Class 2(F2) = 59/122=48.4%
  Class 3(F3-F4) = 38/69=55.1%

- The Accuracy for algorithm

$$\text{Accuracy} = \frac{359 + 59 + 38}{583} = 78.2\%$$

- Weighted Average precision

$$\text{WAP} = \left(\frac{359}{583}\right)(89.1\%) + \left(\frac{59}{583}\right)(49.6\%) + \left(\frac{38}{583}\right)(62.3\%) = 0.548 + 0.050 + 0.040 = 0.639$$

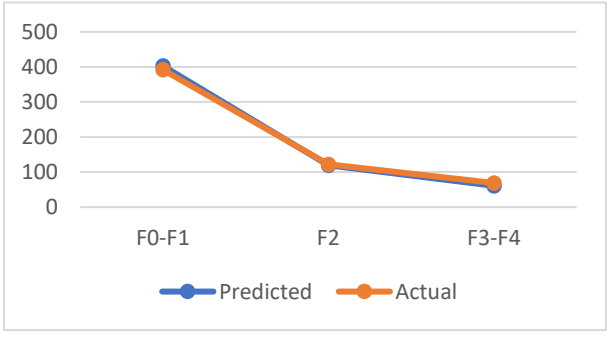

Fig. 14 Actual Vs. Predicted using KNN

3.6.4 Naive Bayes Algorithm

From the confusion matrix that is seen in Table. 5 and Figure 15, from 583 elements. The predicted elements were 370, 108 and 105.

Table 5 Confusion matrix for the comparison between the actual and the predicted cirrhosis levels using Naive Bayes

		Predicted			
		F0-F1	**F2**	**F3-F4**	**∑**
Actual	**F0-F1**	321	41	30	**392**
	F2	43	44	35	**122**
	F3-F4	6	23	40	**69**
	∑	**370**	**108**	**105**	**583**

- The precision for each
  Class 1 (F0-F1) = 321/370=86.8%
  Class 2 (F2) = 44/108=40.7%
  Class 3 (F3-F4) = 40/105=38.1%

- The Recall for each class
  Class 1(F0-F1) = 321/392=81.9%
  Class 2(F2) = 44/122=36.1%
  Class 3(F3-F4) = 40/69=58%

- The Accuracy for algorithm
  $$\boldsymbol{Accuracy} = \frac{321 + 44 + 40}{583} = \mathbf{69.5}\%$$

- Calculate weighted Average precision
  $$\text{WAP} = \left(\frac{321}{583}\right)(86.8\%) + \left(\frac{44}{583}\right)(40.7\%) + \left(\frac{40}{583}\right)83.1 = 0.477 + 0.030 + 0.026 = 0.534$$

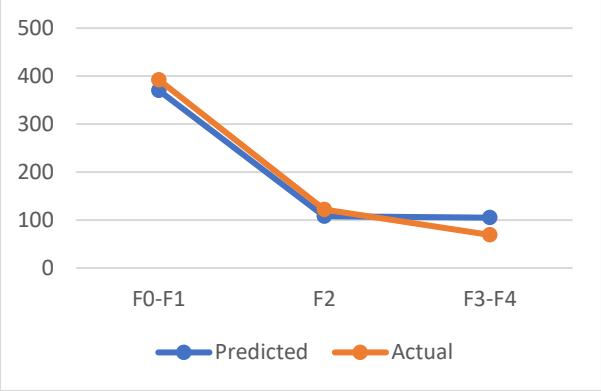

Fig. 15 Actual Vs. Predicted using Naive Bayes

3.6.5 Gradient Boosting

From the confusion matrix that is seen in Table. 6 and Figure 16, from 583 elements. The predicted elements were 400, 121 and 62.

Table 6 Confusion matrix for the comparison between the actual and the predicted cirrhosis using Gradient Boosting

		Predicted			
		F0-F1	**F2**	**F3-F4**	**∑**
Actual	**F0-F1**	374	16	2	**392**
	F2	25	82	15	**122**
	F3-F4	1	23	45	**69**
	∑	**400**	**121**	**62**	**583**

- The precision for each class
  Class 1 (F0-F1) = 374/400=93.5%
  Class 2 (F2) = 82/121=67.8%
  Class 3 (F3-F4) = 45/62=72.6%

- The Recall for each class
  Class 1(F0-F1) = 374/392=95.4%
  Class 2(F2) = 82/122=67.2%
  Class 3(F3-F4) = 45/69=65.2%

- The Accuracy for algorithm
  $$\text{Accuracy} = \frac{374 + 82 + 45}{583} = 86\%$$

- Weighted Average precision
  $$\text{WAP} = \left(\frac{374}{583}\right)(93.5\%) + \left(\frac{82}{583}\right)(67.8\%) + \left(\frac{45}{583}\right)(72.6\%) = 0.599 + 0.095 + 0.056 = 0.751$$

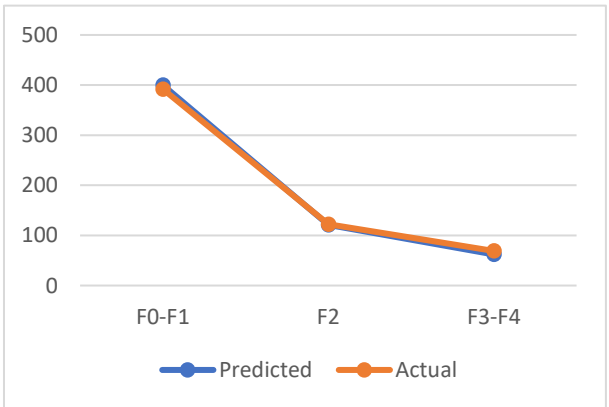

Fig. 16 Actual Vs. Predicted using Gradient Boosting

3.8.Executing Algorithms for testing dataset

A sample of prediction results for the testing dataset is represented in Table 7, where Liver Lab Tests are illustrated, followed by the actual results for the liver cirrhosis class, followed by the prediction algorithm results

Table 7 Sample of prediction algorithms results

Liver lab tests								Actual cirrhosis	The Prediction for model algorithms				
Age	TB	DB	Alkphos	SGPT	SGOT	ALB	PLT		Gradient Boosting	kNN	ANN	SVM	Naive Bayes
22	6.7	3.2	850	154	248	2.8	125	F2	F2	F2	F3-F4	F3-F4	F0-F1
46	20	10	254	140	540	3	455	F2	F2	F2	F3-F4	F2	F0-F1
60	0.7	0.2	171	31	26	3.5	233	F3-F4	F3-F4	F3-F4	F2	F3-F4	F2
45	2.2	1.6	320	37	48	3.4	234	F3-F4	F3-F4	F3-F4	F2	F2	F0-F1
65	0.7	0.2	406	24	45	3.5	156	F3-F4	F3-F4	F3-F4	F2	F3-F4	F2
46	1.4	0.4	298	509	623	1	125	F0-F1	F0-F1	F0-F1	F2	F2	F0-F1

4. RESULTS

in this section, based on the above results that had been obtained in the experimental phase for learning dataset and testing dataset, section 3 is proposed.

4.1 Learning dataset results

Figures 17–19, illustrate the performance of the algorithms used at all classification thresholds as represented by a Receiver Operating Characteristic (ROC) curve. ROC is a widely used measure for evaluating the performance of classification models and is generated by plotting the rate of true positive values (TPR) against the rate of false positive values (FPR) at different classification thresholds. TPR is the proportion of positive cases that are correctly classified, while FPR is the proportion of negative cases that are incorrectly classified as positive.

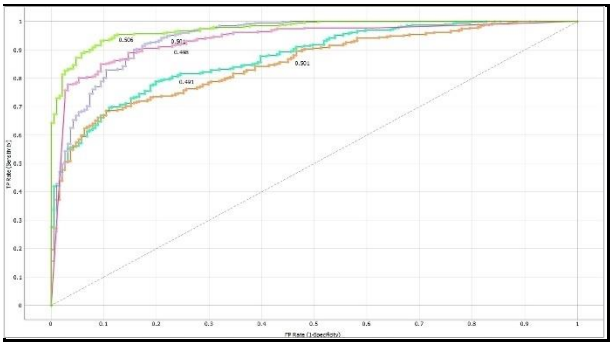

Fig. 17 ROC for Class1 "F0-F1"

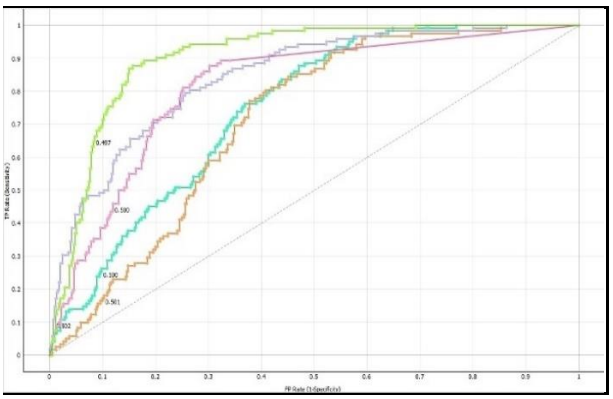

Fig. 18 ROC for Class2 "F2"

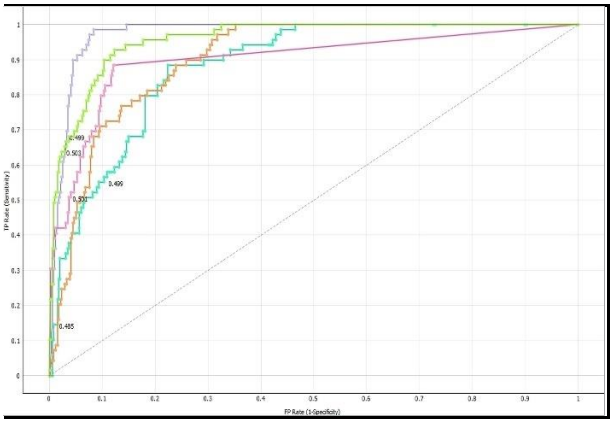

Fig. 19 ROC for Class3 "F3-F4"

As seen in Table 8, based on the learning dataset, the gradient boosting algorithm is the best algorithm with an accuracy of 86%, followed by the neural network, Knn, Naïve Bayes, and finally SVM with an accuracy of 83%, 78%, 68%, and 67% sequentially.

Table 8 Experimental Models Accuracy "Acc" for learning dataset

Model	Acc.		Precision	Recall
Neural Network	83.4%	Class 1	88.1%	96.7%
		Class 2	66.7%	41.0%
		Class 3	73.1%	82.6%
SVM	68.6%	Class 1	77.3%	89.3%
		Class 2	32.7%	27.0%
		Class 3	58.6%	24.6%
Knn	78.2%	Class 1	89.1%	91.6%
		Class 2	49.6%	48.4%
		Class 3	62.3%	55.1%
Naïve Bayes	69.5%	Class 1	86.8%	81.9%
		Class 2	40.7%	36.1%
		Class 3	38.1%	58.0%
Gradient Boosting	86%	Class 1	93.5%	95.4%
		Class 2	67.8%	67.2%
		Class 3	72.6%	65.2%

4.2 Testing dataset results

The confusion matrix and algorithm accuracy are presented in Table 9 for the testing dataset. As seen, the gradient boosting algorithm predicted all classes with an accuracy of 100%, followed by the neural network with an accuracy of 99.20%.

Table 9 Confusion Matrix and Accuracy "Acc" for each algorithm for testing dataset

		Predicted			
	Actual	**F0-F1**	**F2**	**F3-F4**	**Acc.**
Gradient Boosting	**F0-F1**	3	0	0	100%
	F2	0	79	0	
	F3-F4	0	0	43	
kNN	**F0-F1**	0	0	0	97.60%
	F2	0	79	0	
	F3-F4	0	0	43	
Neural Network	**F0-F1**	2	0	0	99.20%
	F2	0	79	0	
	F3-F4	0	0	43	
SVM	**F0-F1**	0	3	0	89.60%
	F2	0	75	4	
	F3-F4	0	6	37	
Naive Bayes	**F0-F1**	3	0	0	53.60%
	F2	43	34	2	
	F3-F4	10	3	30	

5. CONCLUSION

The significance of the liver, its activities, and the effects of liver illnesses like cirrhosis are all highlighted by this research. This research studies how machine learning algorithms are used to categorize and forecast the levels of liver cirrhosis. These algorithms are trained on datasets that contain different characteristics of liver laboratory tests and clinical data, in the context of liver cirrhosis. The objective is to create models that can correctly categorize or forecast the severity or course of liver cirrhosis. Support vector machines, neural networks, gradient boosting, k-nearest neighbors, and naive Bayes are the machine learning algorithms that are employed in this research study. Every method has advantages and disadvantages, and based on the particular dataset and task at hand, their performance severely changes. The Gradient Boosting method was discovered to attain the best accuracy for diagnosing liver cirrhosis levels. This shows that, using the traits and data supplied, it could efficiently discriminate between different stages of liver cirrhosis. The model is applied on a dataset of Egyptian liver patients with 9 features. The dataset is separated into learning and testing, 80% and 20% sequentially. The Gradient Boosting algorithm achieves the highest accuracy of 86% for the learning dataset and 100% for the testing dataset. The algorithm with the worst accuracy is SVM during learning with accuracy level of 68.6% whereas, the Naïve Bayes showed the worst accuracy during testing with percentage of 53.6%.

6. FUTURE WORK

We suggest implementing an algorithm that combines meagerly supervised models with image processing for fibro-scan analysis and clinical judgement.

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