Chronic Liver Disease Prediction Analysis Based on the Impact of Life Quality Attributes

Sivakumar D **Manjunath Varchagall** **Ambika L GUsha S**

Abstract: In the fast developing world living style of individuals are twisted a great deal and will impact the strength circumstance of people. The World Health Organization (WHO) insights give data that the endless liver maladies have a massive arrangement of enthusiasm for restorative research attributable to its effect on individual strength. This research study is intended to recognize and analyze the human life quality attributes in forecasting the chronic liver disease with machine learning techniques. The information gathered from the scope of residents living in Bangalore district and the information realistic inside online information storehouse are the contribution to this examination investigation. Classification methods K-means clustering calculation and the C4.5decision tree approaches are utilized in this examination and the accuracy, recall, precision and the F-measures are the measures evaluated to demonstrate the outcomes with the distinctive error measures RMSE, MAE and Kappa measurement esteems. This interminable liver illness forecast process is demonstrated with a precision of 94.36 rates in C4.5 calculation and 93.7 rates with K-implies grouping procedures.

Index Terms: Prediction, Prevention, Chronic Liver disease, K-means Clustering, C4.5 Decision tree, Life quality attributes.

I. INTRODUCTION

Liver is the biggest inside organ and furthermore the biggest organ in human body. It bolsters pretty much every organ in the body and performs numerous fundamental functions, for example, filtering out poisons and destructive synthetic compounds [1]. Without a healthy liver, a person cannot survive. Liver disorder is usually difficult to diagnose because its symptoms can be vague and sometimes easily confused with other health problems. Particular sorts of blood tests (in this alluded as "liver tests", or LTs) are regularly used to assist doctors with determining whether the liver is working properly or not [2][3].

The World Health Organization extended the meaning of wellbeing to incorporate into expansion to the nonattendance of illness, a total condition of physical, mental and social prosperity. Wellbeing related personal satisfaction rises as a device for estimating result from the patient's perspective, joining social, mental, physiological and physical working. Combined using generic and disease-specific instruments can provide more accurate assessment of both the global aspects and the specific features of health related quality life of a specific condition [4]. The assessment of quality life attribute has been done in gastrointestinal diseases and chronic liver disease. It has been accounted for that the nearness of perpetual liver sickness diminish nature of typical wellbeing and the weakening of value wellbeing is obvious while the seriousness of ailment increments. Moreover, statistic factors, for example, age and sexual orientation, liquor, co-bleak sickness, infection mindfulness and mental status can influence quality life in keep up better wellbeing. Be that as it may, an ongoing report demonstrated that dynamic mental ailment and restorative co-morbidities, yet not seriousness of liver sickness, were determinants of wellbeing quality decrease. Past examines of wellbeing related quality life in ordinary and endless ailments demonstrated that financial and statistic elements can impact quality wellbeing condition [5] [6]. The commitment of financial components and wellbeing recognition to quality wellbeing was not known in basic liver ailment.

Self-rating quiet wellbeing observation is one of the most grounded indicators of mortality. Wellbeing quality in ceaseless liver illness might be improved by changing patient wellbeing recognition if there is a connection between wellbeing discernment and quality wellbeing [7]. The effect of conjugal status in keeping up quality wellbeing is our advantage since its noteworthiness had never been concentrated in perpetual liver malady. The fundamental supposition that was hitched couple would have more psychosocial and passionate help than single, unmarried or separated from individuals. A prior investigation uncovered that wellbeing related quality life in patients with endless liver illness was lower than that of typical subjects like the reports from Western nations [8]. It is intended to explore factors that really influenced quality wellbeing, for example, sickness seriousness, etiology of liver disease, statistic and financial components, and patient wellbeing recognition patients with chronic liver disease [9]. Machine learning and data mining tools are used by numerous researchers to support the health care professional and common human being in forecasting the cardio vascular chronic liver disease. Data mining technique plays a significant task in the intelligent early forecasting medical systems [10] [11]. The relationship of disarranges and the veritable reason of the scatters and the results of manifestations are rashly distinguished from patients are for the most part inspected effectively through the product.

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Data about the hazard factors associated with heart disease bolsters medicinal services experts to distinguish and perceive the patients with most astounding risk of heart sickness[12]. There is a thriving of inconspicuous realities in these records that are generally unexploited by means of information mining can be moved into significant data that can allow human services proficient to take snappy and better therapeutic choices [13][14]. The rule objective of this examination investigation is to investigate the effect of human way of life factors in making cardio vascular sickness, prior gauging and avoidance techniques by keeping up the dimension of way of life factors in precise level.

II. LITERATURE REVIEW

B. Tapas Ranjan etal[15] proposed to anticipate accuracy of liver disease using case-based reasoning and arrangement and relapse tree approach. He likewise], proposed to decide if patients experience the ill effects of liver sickness or not utilizing case-based thinking, counterfeit neural systems and systematic chain of importance strategies [16]. They also predict which kinds of liver illness endured human body.

Abdalla Zidan ng et al.,[17] proposed to determination early Liver infection and anticipate order exactness by coordinated case-based thinking into grouping and regression tree, back-propagation neural system (BPN), prejudicial investigation and logistic regression of characterization strategies in information mining methods. In their strategies they are using ten times cross-approval to choose a best.

Heba Ayeldeen et al, [18] have proposed medicinal determination of liver malignancy using classification strategies. They have utilized choice tree acceptance J48 calculation to characterize liver patient dataset. The dataset is taken from Pt. B. D. Sharma Postgraduate Institute of Medical Science, Rohtak. WEKA information mining tool has been utilized for the preparing of data [19]. The result got demonstrates that the execution of J48 calculation is superior to other classification calculations.

R. Thangarajan et al, [20]has proposed "Liver Prediction Using Bayesian Classification". He has utilized Naïve Bayes and FT tree characterization procedures to group the liver patient dataset into four classes for example liver malignant growth, cirrhosis, hepatitis and no malady. He has utilized WEKA information digging apparatuses for the preparing of data. The test results demonstrate that Naïve Bayes gives preferred execution over FT tree with a precision of 75.54%

Sajida Perveen et al, [21] proposed "Liver Patient Classification utilizing Intelligent Techniques". They utilized J-48 classifier, Multilayer Perceptron classifier, Random Forest classifier, Support Vector Machine classifier and Bayesian Network classifier for order of liver patient information. ILPD dataset accessible on UCI Repository is utilized for assessment [22]. Execution investigation is finished using WEKA tool. Highlight determination system otherwise called Variable choice or credit choice is used to diminish the quantity of highlights with keeping up great outcome.

Sushruta Mishra1 et al [23] anticipated a hepatitis visualization malady utilizing Support Vector machine (SVM) and Wrapper Method. Before characterization process they utilized wrapper strategies to evacuate the clamor highlights. Initially SVM completed component determination to show signs of improvement accuracy. Features selection were implemented to minimize noisy or irrelevance data. From the experimental results they observed the increased accuracy rate in the clinical lab test cost with minimum execution time [24]. They have accomplished the objective by joining Wrappers Method and SVM strategies.

Kotronen AI et al,[25] developed optimizing the classification accuracy when analyzing some medical datasets. This proposed work done by new meta-heuristic approach, called the Homogeneity-Based Algorithm (or HBA).This approach used to predict error rates and associated penalty costs. These costs may be dramatically different in medical applications as the implications of having a false-positive and a false-negative case may be tremendously different.

III. SYSTEM DESIGN AND IMPLEMENTATION

The functional block diagram includes components and the process involved in this research study and analysis are shown in the fig.1. The data is stored in an archive which can suit more data identified with preparing and testing the framework. This archive can store more volume of information for better forecast framework.

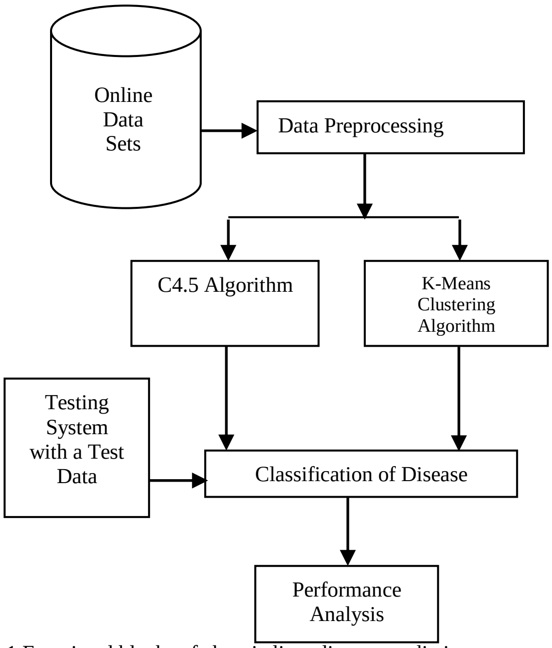

Fig. 1 Functional blocks of chronic liver disease prediction system

The data available from the online repository is considered for the study and analysis. This data consists of more than several attributes such as family history of liver disease, consumption of alcohol, smoking, intake of contaminated food, diabetes and obesity etc. Data preprocessing is performed to make the data, suitable to use with the data mining techniques. The c4.5 algorithm, K-means clustering techniques are the techniques [26] [27] used in this research analysis. These attributes are used to train and develop the system in the motive of detection and the prevention of liver disease. These attributes play an important role in diagnosing liver disease depending on the impact of liver diseases attribute.

The information considered is in the proportion of 80:20 for preparing and testing chronic liver disease forecast framework. Weightage of huge example and the order strategies are surrounded then the C4.5 choice tree model is created for further investigation and examination. K-implies grouping strategy is utilized for making bunching model and the model execution is dissected utilizing distinctive accuracy estimates, for example, precision, recall and specificity. The table I provides the life quality attributes used in this research study and analysis.

I.Life Quality Attributes and Its Ranges

S.No	Life Quality Attribute	Ranges	Risk Level
1.	Age	Less than 35	2
		36 to 45	3
		46 to 65	4
		Above 65	5
2.	Gender	Female	3
		Male	5
3.	Blood pressure (mm Hg)	Normal(130/89)	3
		Low(<119/79)	4
		High(>180/120)	5
4.	Habits	Smoking	3
		Alcohol	4
		Chewing	5
		Hot beverage	2
5.	Stress	No emotion control	2
		Rare control	4
		Heavy control on emotions	5
6.	Blood Sugar Level	High(120 to 400)	5
		Normal (90 to 120)	2
		Low (Less than 90)	3
7.	Financial Burdon	No	3
		Normal	2
		High	5
8.	Body Over Weight	Yes	3
		No	1
9.	Marital Status	Married	5
		Single	2
10.	Past History of hepatitis	No hepatitis	1
		Chronic hepatitis	3
		Viral hepatitis B	5
11.	Quality Food Habit	Vegetarian	2
		Non-Vegetarian	4
12.	Physical Activity	Less	5
		Medium	3
		Heavy	1
13.	Education	Degree holder	1
		Schooling / Diploma	2
		Illiterate	3
14.	Bad Cholesterol Level	Normal (Less than 160)	2
		High (160 to 200)	4
		Very High (Above 200)	5
15.	Profession	White-collar	2
		Blue-collar	3
		Unemployed	4

A. K-means Clustering Technique

The data set that creates chronic liver disease and the data sets that do not generate chronic disease are categorized by implementing k-means clustering technique. The noteworthy example weightage is determined independently and its mean esteem is used to distinguish the underlying focal point of the bunch [28]. In this method the estimation of 'k' signifies the groups and the estimation of 'D' speaks to the informational collections with 'n' objects. These two qualities are given as a contribution to the k-implies bunching method calculation and the yield is the hierarchical cluster represented with the term 'A'. As an initial step of this procedure pick the arrangement of mean extents from the noteworthy example weightage and distinguish the beginning or starting position of the bunch focus [29] [30]. In second step the mean value of significant pattern weightage and accordingly map the most suitable cluster for each object. At that point the cluster implies are refined using the mean estimation of practically all group objects present in the group.

Pseudo Code forK-Means Algorithm

Input: Let X={x1, x2, x3,…………… xn} be the set of data points and V={v1, v2, v3,…………… vc} be the set of centres.

1. Randomly select ‘c’ cluster centres.
2. Calculate the distance between each data point and cluster centres.
3. Assign the data point to the cluster center is minimum of all the clusters centers
4. Recalculate the new cluster centre using this formula
   $v_i = (1/C_i)\sum_{j=1}^{c_i} x_i$ (1)
   Where C C_i represents the number of data points in i^{th} cluster.
5. Recalculate the distance between each data point and - new obtained cluster centers.
6. If no data points was reassigned then stop, otherwise repeat from step 3.

B. C4.5 Algorithm

The algorithm C4.5 depends on the data gain proportion that is assessed by entropy. The data gain proportion measure is utilized to choose the test highlights at every hub in the tree [31] [32]. Such a measure is alluded to as a component (property) determination measure.

The characteristic with the most astounding data gain proportion is picked as the test include for the present hub. Let D be a set comprising of (D_1… D_j) data examples [33] [34]. Assume the class mark characteristic has m unmistakable qualities characterizing m particular classes, C_i(for I = 1,… ,m). Let Di a chance to be the quantity of tests of D in class C_i. The normal data expected to order a given example is given by

SplitinfoA(D)=- Σ ($|D_j|/|D|$)*log (($|D_j|/|D|$)) (1)

Gain ratio(A)=Gain(A)/Split infoA(D)(2)

Where

Gain= Info(D) – InfoA (D)

Info(D)=- Σ P_i log$_2$(P_i)

and

Info A(D)=- Σ ($|D_j|/|D|$)* Info(D_j)

Where

P_i= probability of distinct class

Ci, D =data Set, A=Sub attribute from attribute, ($|D_j|/|D|$)=act as weight of j[th] partition. In other words, Gain (A) is the expected reduction in entropy caused by knowing the value of feature A.

Pseudo Code for C4.5 Algorithm

INPUT: An attribute valued dataset D

1. Tree={}
2. if D is “Pure” OR other stopping criteria met then
3. Terminate
4. end if
5. for all Attribute a Є D do
6. Compute information-theoretic criteria if we split on a
7. end for
8. a_{best}=Best attribute according to above computed criteria
9. Tree = Create a decision node that tests a_{best} in the root
10. D_v = Induced sub-datasets from D based on a_{best}
11. for all D_v do
12. $Tree_v$=C4.5(D_v)
13. Attach $Tree_v$ to the corresponding branch of tree
14. end for
15. return Tree

IV. RESULTS AND DISCUSSIONS

The performance of the chronic liver disease prediction system is analyzed using three statistical methods called precision, recall, accuracy and F-measure and the mathematical representations are given in the equation (3) to (6). The performance of this system is tested with test data and the accurate and inaccurate categorizations are recognized to estimate the accuracy of the system. The accuracy of this system is calculated with positively and negatively categorized instances.

$$Recall = \frac{True\ Positive(TP)}{True\ Positive(TP) + False\ Negative(FN)} \quad (3)$$

$$Precision = \frac{True\ Positive(TP)}{True\ Positive(TP) + False\ Positive(FP)} \quad (4)$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (5)$$

$$F - Measure = \frac{2 * Recall * Precision}{Precision + Recall} \quad (6)$$

A. Mean Absolute Error

Mathematical representation of mean absolute error (MAE) is provided using the equation (7). It’s the mean test instances of the absolute difference between predicted and actual results.

$$MAE = \frac{1}{N}\sum_{j=1}^{n}|yi - y'i| \quad (7)$$

B. Root Mean Squared Error

The magnitude of root mean squared error (RMSE) is calculated using the equation (8). It’s the square root of the average of squared differences between predicted and actual results.

$$RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(yi - y'i)} \quad (8)$$

C. Kappa Statistics

The equation for estimating kappa statistics is represented in (9). Kappa statistics provides data to recognize the level to which physician persuade with each other further that what you might be expecting to see based on likelihood alone.

$$Kappa = \frac{yi - y'i}{1 - y'i} \quad (9)$$

II. Statistical Values of K-Means Clustering

Cluster	TP	FP	Precision	Recall	F -Measure
Cluster 1	0.967	0.001	0.998	0.998	0.999
Cluster 2	1	0	0.997	1	1
Cluster 3	0.932	0.001	1	0.996	1
Cluster 4	1	0	0.999	1	0.994
Cluster 5	1	0	1	0.992	0.994

The table II provides the statistical values of different measure obtained from the k-means clustering algorithm. The statistical values in the table show that the true positive values are almost one. The false positive values are almost zero or very near to zero and it shows that this methodology provides better early diagnosis of chronic liver disease.

Table III provides the statistical vales different accuracy measures using the C4.5 decision tree approach. In this approach also true positive values are very near to one and the false positives very near to zero. These results also prove that this early diagnosis approach with life quality attributes perform better predicts the chronic liver disease.

III.Statistical Values of C4.5

Cluster	TP	FP	Precision	Recall	F -Measure
Chronic Liver Disease	0.998	0.048	0.963	0.997	0.956
Non Chronic Liver Disease	0.987	0.059	0.997	0.986	0.9492
Weighted average	0.979	0.048	0.988	0.978	0.967

IV.Error Statistics

Cluster	K-Means	C4.5
Root mean squared error (RMS)	0.0254	0.2001
Mean absolute error (MAE)	0.0079	0.1686
Kappa statistic (KS)	0.9647	0.9101

Table IV provides the error measurements generated by the classification mechanisms. It is used to validate the accuracy of the analysis results. Three error measurements are calibrated in this analysis and these error statistics clearly shows that this early diagnosis approach performs better in prediction of chronic liver disease

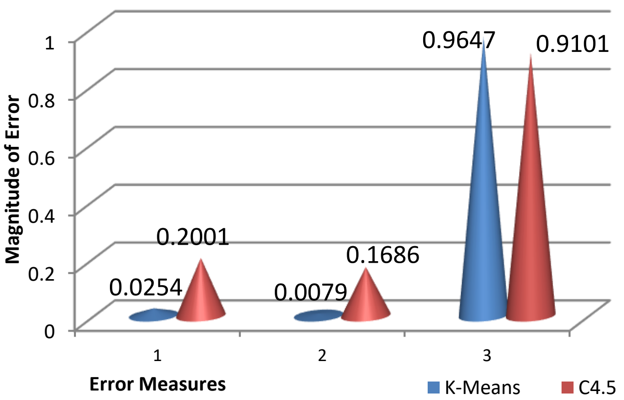

Fig. 2 Error measures representations

The pictorial representation of the error measurements are shown in fig.2. This representation clearly shows that k-means technique generates less RMSE when compared to decision tree approach. The next error measure kappa statistic is more for k-means technique when compared to decision tree approach.

V.Accuracy Measures

Cluster	K-Means	C4.5
Accuracy	93.47%	94..36%

Table V provides the statistical measures of the classification accuracy calculated using k-means and C4.5 decision tree mechanisms. There is no major difference in accuracy value of the k-means and C4.5 decision tree mechanism but comparatively C4.5 provides better results.

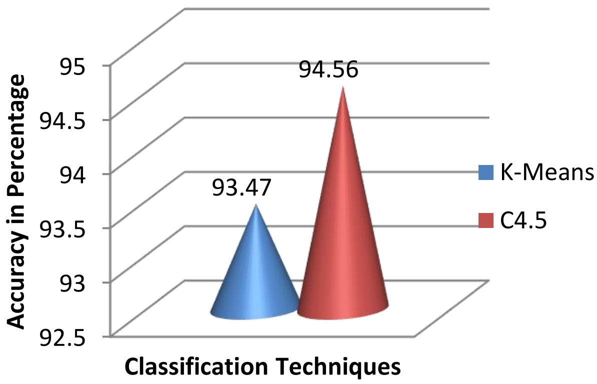

Fig. 3Accuracy representations

Classification technique accuracy is graphically represented through the figure 3. These representation shows that the c4.5 method provides better and accurate results when compared to K-means. This is because of the type and range of data stored in different clusters and the data used in decision tree mechanism

V. CONCLUSION

Life quality factors and their ranges with different level of risk are the major key factors considered in this analysis. The classification techniques k-means clustering algorithm and the c4.5 decision tree mechanism are used in this analysis for better prediction of chronic liver disease. The 15 life quality attributes in addition to the c4.5 technique provide a better accuracy when compared to K-means clustering method. This analysis helps the patient and the physician for cost effective and early forecasting of chronic liver disease. And the level of risk identified in this analysis will help the patient to maintain health free from chronic liver disease. Further refining of life quality attributes and the frame work creation for early diagnosis for multiple diseases are the further development of this analysis.

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