Infrared Sensing Based Non-invasive Initial Diagnosis of Chronic Liver Disease Using Ensemble Learning

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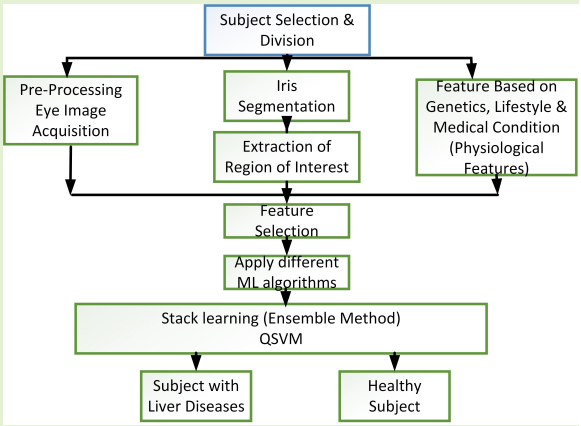
***Abstract*— The liver is a vital human body organ and its functionality can be degraded by several diseases such as hepatitis, fatty liver disease, and liver cancer and so forth. Hence, the early diagnosis of liver diseases is extremely crucial for saving human lives. With the rapid development of multimedia technology, it is now possible to design and implement a non-invasive system that can chronic liver diseases. For this purpose, machine learning and Artificial Intelligence (AI) have been used within the past few years. In this regard, digital image processing supported by AI methods has been implemented in the diagnosis of diseases that also showed high reliability. Therefore, in this paper, an iris feature-based non-invasive technique is proposed by incorporating a novel machine-learning algorithm. The experimental setup involved data set for the models' training included 879 subjects from Pakistan, of which 453 subjects have chronic liver disease and 426 are healthy. The iris images were collected using an infrared camera that consists of a lens, a thermal sensor and digital electronics processing. The lens focuses on the infrared energy on the sensor, using distinctive forms of features twenty-two physiological and thirty-three iris features. The designed classification model for a non-invasive system combined eleven different classifiers and used cross-validation techniques for comparing the results. The overall performance of the model was analyzed using five parameters: accuracy, precision, F-score, specificity, and sensitivity. The results confirmed that the proposed non-invasive model is capable of predicting chronic liver diseases with 98% of accuracy.**



***Index Terms*— Artificial Intelligence; Chronic Liver Disease; Computer-Aided Diagnosis; Complementary Medicine Technique; Ensemble Classification; Iridology; Machine Learning; Stack learning; Thermal Sensor**

I. Introduction

The early diagnosis of a disease is vital in medical science as timely diagnosis followed by treatment and precaution can save human lives. In this regard, Computer-Aided Diagnosis (CAD), also called Complementary Medicine Technique (CMT), supported by Artificial Intelligence (AI) is appearing to be reliable, indispensable, robust, and accurate. CAD/CMT is gaining significant popularity as a diagnostic tool, especially for such diseases where the mainstream diagnosis is painful and less precise. Further, because of the reliability and accuracy, proliferated utilization of CAD/CMT has been observed. The same has further been supported by Haaris et al., and it was stated that 38% and 52% general population use CAD/CMT based diagnostic techniques in the United States of America (USA) and Australia, respectively [1].

Further, AI has helped medical practitioners in reducing the errors in the diagnosis of diseases and increase precision [2]–[7]. In return, it has saved the vital organ of the human body. AI has enabled early diagnosis of various diseases such as breast cancer [8], [9], virus diseases [10], Alzheimer's disease [11], [12], and cardiovascular diseases [13]–[17] . Keeping in mind the accuracy and reliability offered by these AI-based diagnostic techniques, many researchers have worked on various disease diagnosis. However, there are limitations associated with these CAD systems, as mentioned below:

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1) Smaller database restricts the performance of classifiers
2) Fewer data features result in loss of information
3) Ability to deal with inter-patient variability
4) Higher computational cost
5) Higher execution time

The proposed work has incorporated a comparatively new AI approach, known as the ensemble learning method, to overcome the limitations mentioned above. Various research has been published that involves ensemble learning method, and this approach has been successful in getting rid of the limitation associated with conventional Machine Learning (ML) models [18]–[24]. Further, data type and its features also play a vital role in defining the classifier's performance. Therefore, the presented work has been focused on diagnosing liver disease using iris and physiological features. The iris features were extracted from the grey-level infrared image capturing using an infrared sensor-based camera. Various researchers have worked on clinical and psychological features, especially by using conventional ML models. However, iridology has rarely been incorporated in the diagnosis of liver disease.

In the field of CAD, iridology is an emerging diagnostic tool, and it makes use of patterns, structures, texture, colour, and other related features of the iris to estimate the health condition of patients. Jensen et al. presented an iridology chart and linked 80-90 zones of iris with different organs of the human body [25]. Iridology believes that estimating the health condition and working of vital human organs is possible by linking the minute details available in the iris. Iridologists used to observe these patterns and details of the iris and assess the disease manually. However, with the development of infrared sensing and advanced computer vision techniques and AI algorithms, converting these details available in the iris into meaningful data for disease diagnosis has become faster and accurate.

The rich textural characteristics of the iris make it a useful diagnostic tool in the field of pathology. Through contraction and dilation, the iris controls the light entering the eye. Dilator and sphincter muscles control the iris's size by regulating the amount of light entering the pupil. Further, any significant change in health condition is commonly directed toward dilator. Hence, the iris's sphincter muscle can provide meaningful information related to complex non-linear deformation in the iris.

The anatomical characteristics of the iris highlight the blood circulation system and functional changes of organs. [27]. Ma et al. presented a medical analysis [28] using the iris's geometrical features. Geometrical features included pupil largeness, pupil roundness, and roundness of collarette boundaries. The result showed significant accuracy in the diagnosis of disease. Hussein et al. presented an iris-based diagnosis of kidney disease using wavelet features, and an Adaptive Neuro-Fuzzy Inference System [29]. Results showed 93% and 82% correct classification for both normal subjects and kidney problems, respectively. Ramlee et al. presented an iris-based mechanism to estimate the cholesterol in blood vessels [30], [31]. Bansal et al. also developed an iris-based diagnostic tool for diabetes [32]. The presented model was based on wavelet features, and the machine learning algorithm was Support Vector Machine (SVM). Similarly, various other models for diabetes diagnosis were presented in recent years by researchers [33]–[39]. Hence, iridology has established its effectiveness in the non-invasive early diagnosis of diseases. Despite that, iridology has very rarely been analyzed and researched for the non-invasive early intervening of liver diseases.

Being a vital organ of the human body, the liver has emphasized various researchers worldwide to design its non-invasive AI-based diagnostic technique. Hepatocellular carcinoma (HCC) is one of the most common types of liver cancer; in this regard, various AI-based diagnoses have been presented by the research community. To predict the HCC, a support vector machines (SVM) based machine learning model was presented by Ksiazek et al. [40]. The presented model achieved an accuracy of 88.49% in diagnosing HCC using 165 subjects. Nayak et al. presented an SVM-based non-invasive diagnosis of HCC using computed tomography (CT) images [41]. The model was trained on twenty-four features of forty CT images. The model was successful in achieving an accuracy of 80%. Another research incorporating textural features was presented by Brehar et al. [42]. Accuracy of 72% was attained using adaptive boosted classifiers in diagnosing HCC. A research work incorporating neural network (NN) and logistic regression (LR) classification models was presented by Santos et al. [43]. CHUC database was used, and 75.2% and 73% accuracies were observed for NN and LR, respectively. Sawhney et al. also published a work on feature selection methods for cancer using the firefly algorithm (FFA) [44]. Accuracy of 83.5% was achieved by using a random forest classifier and CHCU database.

Lin et al. presented an intelligent model for the diagnosis of liver disease. Model incorporated classification and regression tree (CART) [45]. Presented work was further modified in [46] where CART was replaced with NN and health and lifestyle information as data features were added with LFT result and demographic information. Another diagnosis model for liver disease was presented by Zhou et al., which incorporated a glowworm swarm optimization (GSO) algorithm. In order to improve the accuracy, the presented work also used support vector data description (SVDD) and data visualization techniques. Another review was presented involving comparative analysis of various machine learning algorithms [47], [48]. Results concluded that random-forest (RF) produced the best result in liver disease diagnosis with the balanced data. Another study was published by Abdar et al. that incorporated two algorithms named Boosted C5.0 and CHAID algorithms [49]. Results claimed to achieve 93.75% accuracy with boosted C5.0 algorithm.

Chang et al. presented an intelligent model for chronic liver disease diagnosis [50]. Principal component analysis (PCA), a well-known technique, was used for dimension reduction of data, followed by an Artificial Neural Network (ANN) classifier. Acharya et al. worked on a hybrid model by utilizing three different algorithms [51]. Linear discriminant analysis (LDA) was used to reduce the features, SVM was Incorporated as a classifier, and GA was used to optimize the model to achieve an accuracy of 90.3%.

The presented ensemble model for non-invasive early di-

agnosis of liver disease has incorporated a novel approach of diagnosis using iris and physiological features. Overall, the feature vector (FV) consists of 55 features including iris (GLCM, GLRL & Statistical), physiological features. Further, the data set incorporated in a study plays a vital role in defining the AI model's accuracy. Unlike the models covered in the literature, the presented work acquired primary data from 789 patients from three different hospitals in Islamabad/Rawalpindi, Pakistan. The accuracy of the presented AI-based non-invasive liver disease diagnosis was better than existing models. A detailed comparison is given in section: Result & Discussion. The detailed contribution of work is as follows:

1) Novel approach of combining iris and physiological features for liver disease diagnosis has opted.
2) Primary data from 879 patients were collected from three different hospitals of Islamabad/Rawalpindi, Pakistan.
3) Eleven state-of-the-art classifiers from different families of classification models were analyzed for the chronic liver disease diagnosis
4) To increase the accuracy, multiple classifiers were combined using stack learning (ensemble method).
5) To obtain high data quality, K-Nearest Neighbour (KNN) algorithm was used to fill the missing value in physiological features.

II. Materials and Methods

The presented non-invasive diagnosis for chronic liver disease using an ensemble classification model works on the iris and physiological features. Further, eleven different state-of-the-art ML algorithms were combined using stack learning. A complete block diagram has been shown in Fig. 1, and each block is separately explained in the following subsections.

A. Subject Selection for Data Acquisition

With the consent of subjects and approval of concerned doctors, a primary data set, including two different types of data (iris and physiological), was acquired from 879 subjects. Out of these subjects. 453 subjects were labelled as the subject with chronic liver disease, supported by the liver function test (LFT) and doctor's prescription. On the other hand, 426 subjects were classified as healthy subjects. Details of the subject under consideration are given in Table I.

B. Physiological Features

Physiological features have also shown significant performance in disease diagnosis. These features and Machine Learning (ML) techniques have achieved high accuracy and reliability for various disease diagnoses [52], [53]. Work on the prediction of type 2 diabetes, based on physiological features and more than 2500 subjects was presented by Heydari et al. [52]. Further, a comprehensive analysis on the significance and performance of computational techniques to predict diabetes was presented by Dwivedi [53]. The study incorporated the Pima Indians Diabetes database.

A list of physiological features that were incorporated in this work, along with its type, is given in Table II. It is worth mentioning that 7 out of 22 physiological features were numeric, and these are height, age, weight, systolic blood pressure, diastolic blood pressure, body temperature/fever, and BMI. The rest of the 15 features lies in the category of the nominal features. To incorporate these features in a machine learning algorithm, it is crucial to converting the nominal features into numeric ones using a process known as the continuation. Hence, a binary encoding technique was applied to convert the 16 nominal features into numeric features [54].

1) Missing Values: Due to human error, missing data in physiological features are usually expected. However, a large quantity of such missing values can significantly affect the accuracy of ML algorithms. Therefore, for physiological features, the KNN algorithm was used o fill the mission values. KNN algorithm estimates the missing values with the help of several closest samples. Python imputation library *impyute* was used to implement this part.

C. Eye Image Acquisition

Iris Images of the right eye were collected after testing the empty stomach blood glucose level. Iris images were collected using the I-SCAN 2 of *Cross Match Technologies*, USA. Using the spectroscopy techniques, I-SCAN 2 produced grey-level Infrared IR images. The size of the images was 640*480 pixels. Further, IR spectroscopy has unique usage in the study of tissue breakage, which makes it a suitable choice for the study of iridology-based disease diagnosis [55]. Sample images for both healthy subjects and subjects with chronic liver disease are given in Fig. 2.

D. Pre-Image Processing Techniques

Before extracting features, it is essential to process the images to yield better quality features. Details of pre-image processing techniques were used as given in the following sections:

1) Iris Localization and Segmentation: The Center and radius of the iris's inner and outer circular parts are the iridology's main features. Localization is the process of extracting iris features from the image of the eye, and segmentation is the process of slicing out the localized iris. To segment, the localized iris, the most acknowledged and popular IRIS segmentation technique was incorporated and known as circular hough transformation (CHT) [56].

2) Rubber Sheet Normalization: Before extracting the region of interest (ROI), iris images need to be converted to a rectangular shape from a circular one. However, it is also necessary to avoid the loss of information dimension irregularities and uneven illumination. Therefore, Dougman's rubber sheet model [56] was opted in this research work. The size of the rectangular image section was 360 * 720 pixels.

3) Extraction of Region of Interest (ROI): According to the iridology, chart [25], different human body organs are linked with the various region of left and right images. These regions are highlighted in Figure 3, and scientific analysis can provide vital information regarding human body organs' functionality.

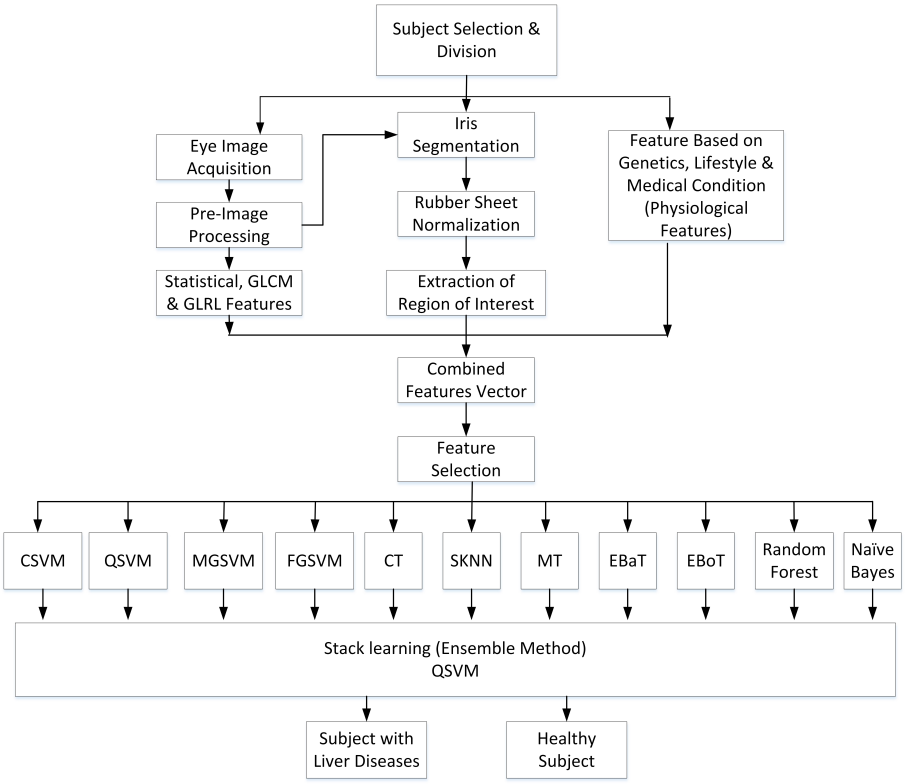

Fig. 1. Block Diagram of Infrared Sensing Based Non-invasive Initial Diagnosis of Chronic Liver Disease Using Ensemble Learning

TABLE I
DETAILED SUBJECT DISTRIBUTION.

	No. of Males	No of Females	Mean Age	Standard Deviation	Total Total
Healthy Subjects	257	169	55.8	8.9	426
Subject with Chronic Liver Disease	293	160	51.8	10.3	453

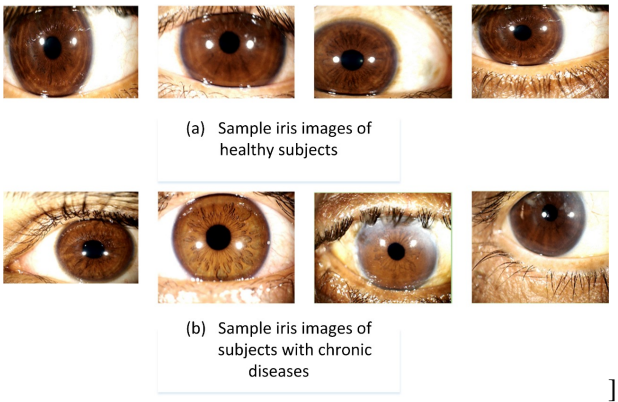

Fig. 2. Sample iris images of both (a) healthy subjects and (b) subjects with chronic liver disease

For the liver, the area between segments 8 and 9 of the right eye iris image is mentioned. Therefore, after converting the circular image to a fixed-sized rectangular image, the liver's ROI was cropped.

E. Extraction of IRIS Features

The presented work used ML algorithms to diagnose liver disease, and ML algorithms learn the classification using data features. Hence, the correctness of data and its features is crucial for an accurate diagnosis. Further, to estimate liver functionality using iridology, iris features involving both statistical features and texture features (GLCM & GLRL) were extracted from the ROI mentioned in the previous section. Details of IRIS features are provided in the following subsections.

F. Statistical Features

Contrast, Skewness, Kurtosis, Standard Deviation (SD), Correlation, Mean Intensity (MI), and Entropy was selected as statistical features as minutes details about the nature of grayscale pixels, along with the grayscale intensities of ROI, can be analyzed using these features.

1) Gray-level Co-occurrence Matrix (GLCM) Features: GLCM is the spatial grey-level dependency matrix to analyze inter-pixel relationships and distribution of grayscale pixel intensities and plays an important role in image processing [26]. The size of GLCM depends on the grey-level intensities;

TABLE II
PHYSIOLOGICAL FEATURES WITH TYPE

Sr. No	Feature Name	Type
1	Age	Numeric
2	Weight	Numeric
3	Height	Numeric
4	BMI	Numeric
5	Sex	Nominal
6	Systolic Blood Pressure	Numeric
7	Diastolic Blood Pressure	Numeric
8	Family History of Diabetes	Nominal
9	History of High Blood Pressure	Nominal
10	History of Using Drugs for High Blood Pressure	Nominal
11	Condition of EYE's Vision	Nominal
12	Fatigue	Nominal
13	Cough	Nominal
14	Shortness of breadth	Nominal
15	Stress at Work	Nominal
16	Exercise or Workout	Nominal
17	Smoking	Nominal
18	Drinking	Nominal
19	Smog Issue in Nearby Area	Nominal
20	Heart/Kidney/Liver Problem	Nominal
21	Taking Medicine for Chronic Disease	Nominal
22	Body's Temperature/Fever	Numeric

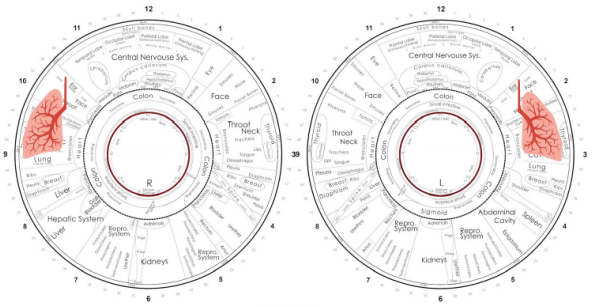

Fig. 3. Relationship Between Left & Right Iris Images and Liver of Human Body Using Iridology Chart

if there are S grey-level intensities in an IRIS image, then GLCM will be a *S*S* matrix as the number of possible pairs of grey-level intensities will be *S*S*. Hence, the number of occurrences of each pair will be stored in GLCM. 19 GLCM based features extracted for the presented diagnostic technique, as mentioned below:

1) Difference Variance
2) Sum of Squares Variance
3) Difference Entropy
4) Homogeneity
5) Sum Average
6) Correlation
7) Information Measure of Correlation 1
8) Information Measure of Correlation 2
9) Auto Correlation
10) Maximum Probability
11) Contrast
12) Dissimilarity
13) Cluster Shade
14) Cluster Prominence
15) Sum Entropy
16) Energy
17) Inverse Difference
18) Sum Variance
19) Entropy

2) Gray-level Run Length (GLRL) Matrix Feature: For texture analysis, the GLRL matrix has its importance, especially for extracting higher-order statistical texture features [57], [58]. A line of pixels with the same intensity in a specific direction is defined as the GLRL matrix, and the frequency of occurrence is known as the run-length value. The number of neighboring pixels with the same intensity of grey level in a particular direction is considered as the run length. Seven GLRLM features have been extracted for the presented work, and these are mentioned below. These features were extracted using equations 1-7.

1) Short Run Emphasis (SRE)
2) Long Run Emphasis (LRE)
3) Gray level non-uniformity (GLN)
4) Run-length non-uniformity (RLN)
5) Low Gray Level Run Emphasis (LGLRE)
6) Run Percentage (RP)
7) High Gray Level Run Emphasis (HGLRE).

$$SRE = \sum_{i=1}^{G}\sum_{j=1}^{R}\frac{p(i,j|\theta)}{j^2} / \sum_{i=1}^{G}\sum_{j=1}^{R}\frac{p(i,j|\theta)}{1} \tag{1}$$

$$LRE = \sum_{i=1}^{G}\sum_{j=1}^{R} j^2 \times p(i,j|\theta) / \sum_{j=1}^{R} p(i,j|\theta) \tag{2}$$

$$GLN = \sum_{i=1}^{G}(\sum_{j=1}^{R} p(i,j|\theta))^2 / \sum_{i=1}^{G}\sum_{j=1}^{R} p(i,j|\theta) \tag{3}$$

$$RLN = \sum_{j=1}^{R}(\sum_{i=1}^{G} p(i,j|\theta))^2 / \sum_{i=1}^{G}\sum_{j=1}^{R} p(i,j|\theta) \tag{4}$$

$$LGLRE = \sum_{i=1}^{G}\sum_{j=1}^{R}\frac{p(i,j|\theta)}{i^2} / \sum_{i=1}^{G}\sum_{j=1}^{R}\frac{p(i,j|\theta)}{1} \tag{5}$$

$$RP = \frac{1}{N}\sum_{i=1}^{G}\sum_{j=1}^{R} p(i,j|\theta) \tag{6}$$

$$HGLRE = \sum_{i=1}^{G}\sum_{j=1}^{R} i^2 p(i,j|\theta) / \sum_{i=1}^{G}\sum_{j=1}^{R} p(i,j|\theta) \tag{7}$$

Hence, to analyze the condition of tissues in IRIS, seven statistical, nineteen GLCM, and seven GLRL matrix features were extracted from one ROI, making a total of 33 features. Further, these features were processed by the classification algorithms to diagnose liver disease, as discussed in detail in the section later on.

G. Feature Selection

As mentioned before, there is only one ROI from the right eye for liver diagnosis. Therefore, from the single subject, 55 features incorporating 33 iris features and 22 physiological features were extracted. However, it is imperative to reduce the computational complexity by removing the redundant features, which increases the classification reliability. In this regard, two filter-based feature selection methods were incorporated, and these are Student's t-test and PCA. Both the aforementioned feature selection methods are computationally efficient, well-known, and straightforward for biomedical applications. Further details are given in the following subsections.

1) Student's t-Test: For binary classification *Simple Student's t test* is a well-known technique for feature selection. It calculates the class means difference and variability to differentiate the two classes. The presented model has included the student's t-test technique for feature selection [59].

Principal Component Analysis

PCA is a widely known statistical tool. Using orthogonal transformation, it has its prominent utilization in converting highly correlated variables into linear uncorrelated variables [60].

H. Classification

Classification is supervised learning where test data and labels play an important role in deciding the output. Further, the nature, type, and complexity of the data set also link classifiers' performance and accuracy. Therefore, a detailed analysis of data is crucial while selecting the classifiers. Overall, eleven different classifiers were incorporated from different families of classifiers, as mentioned below:

1) Cubic Support Vector Machine (CSVM)
2) Median Gaussian Support Vector Machine (MGSVM)
3) Quadratic Support Vector Machine (QSVM)
4) Fine Gaussian Support Vector Machine (FGSVM)
5) Boosted Tree (EBOT)
6) Bagged Tree (EBAT)
7) Subspace K-Nearest Neighbour (SKNN)
8) Complex Tree (CT)
9) Median Tree (MT)
10) Naive Bayes Classifier Algorithm
11) Random Forest

Further, it is also worth highlighting that to enhance the performance of overall liver disease diagnosis, these eleven classifiers were combined using stack learning (ensemble method), as shown in Fig. 1. This approach has further elevated the accuracy of diagnosis of liver disease.

Understanding and highlighting each parameter of the classifiers mentioned earlier is challenging as these classifiers belong to different statistics and computer science groups. Further, manual selection of parameters can lead to biasing. Hence, to optimize the performance of classifiers, the cross-validation technique was utilized for parameter selection. The model was trained using the repetitive iteration technique, and the 10-fold cross-validation method was used for validation, and complete data were divided into ten distinct groups. The model was trained using 9 data groups and tested with the remaining 1 data group. The model was trained by repeating the same procedure, and one data group was used only once for validation/testing purposes and nine times for training purposes. Finally, results were computed using the average of all the iterations.

I. Ensemble Learning (Classification) and Stacking Learning

To increase the accuracy and better predictive performance, ensemble learning is used to combine multiple classifiers in one model [61]. There are multiple ensemble learning techniques; however, the presented work opted stack learning technique that combines multiple classifiers via meta classifier. The stack learning model presented in this work consists of two layers. In the first layer, eleven state-of-the-art classifiers of the AI domain were used and these classifiers were trained using the data of 879 subjects as mentioned before. Subsequently, eleven classifiers returned the probability of belonging to both classes which are subjects with chronic liver disease and healthy subjects. This probability was considered as meta-feature. In the second layer, the QSVM classifier was brought to utilization once again; however, QSVM acts as a meta-classifier in the second layer and is trained by using meta-features. Finally, the output of the meta-classifier classifies the subject under consideration. The overall model of non-invasive diagnosis for chronic liver disease using AI-based ensemble classification model is given as Fig. 1.

It is worth mentioning that for comprehensive analysis, the performance of all eleven classifiers and stack learning model has been presented in the results section. It was observed that the stack learning model outperforms all eleven classifiers.

III. Experimental Setup

The data selection techniques and machine learning classifiers were implemented in Python language and executed on NVIDIA's embedded Tegra K1 SoC (CPU+GPU+ISP on a single processor). Jetson is a low-power system and is designed for accelerating machine learning applications. An operating system used for this platform was Ubuntu, a Debian-based Linux operating system [62]. NVIDIA's embedded Tegra K1 typically comes pre-installed with Linux4 Tegra OS (basically Ubuntu 14.04 with pre-configured drivers). Iris images were collected using the I-SCAN 2 of Cross Match Technologies, the USA with the resolution of 640×480. Machine learning models were developed using Python 3.7 and the following libraries were used:

1) Impyute
2) Sklearn
3) StakingClassifier
4) Pandas

IV. Results and Discussion

The presented work incorporated eleven different classifiers; hence, first, the performance of these classifiers was

analyzed individually, and subsequently, these classifiers were combined using stack learning (ensemble method) to enhance the accuracy of liver disease diagnosis. The result has shown that the stack learning-based model has further enhanced the performance.

Overall five different parameters were incorporated to evaluate the performance of classifiers. These are Accuracy, Precision, Specificity, Selectivity, F1 Score. However, to calculate these parameters, the following four results are necessary. For better understanding, consider *Class A* as the subject with OLD and *Class B* as healthy subjects.

1) **True Positive (TP):** Number of samples labelled as class A were correctly classified class A
2) **True Negative (TN)**: Number of samples not belonging to class A was correctly classified to class B.
3) **False Positive (FP):** Number of samples labelled as class B was incorrectly classified as class A.
4) **False Negative (FN):** Number of samples labelled as class A was incorrectly classified as other class B.

A. Confusion Matrix

The confusion matrix is designed based on the above-mentioned results which are: *TP*, *TN*, *FP*, and *FN*. The sample structure of a confusion matrix is given in Table. III. The confusion matrix provides a detailed analysis of classification. Further, all the performance indicators are calculated using a confusion matrix. All the classifiers and the stack learning model were individually analyzed using the confusion matrix, and later on, the results were compared using the performance indicators. For comparative analysis, the confusion matrix of the three best classifiers, including the best one *stack learning model* has been included in the paper. CSVM and QSVM were the best classifiers with accuracies of 94% and 95%, respectively. Further, all the classifiers were combined using the stack learning approach, and accuracy was further improved to 98%. Confusion matrix of stack learning model, CSVM, QSVM are given as Table. IV, Table. V, and Table. VI, respectively. Detailed analysis and discussion on results are covered in subsequent sections.

TABLE III
SAMPLE CONFUSION MATRIX

	Positive	**Negative**
Positive Diagnose	TP	FP
Negative Diagnose	FN	TN

TABLE IV
CONFUSION MATRIX OF STACK LEARNING MODEL

	Positive	**Negative**
Positive Diagnose	445	10
Negative Diagnose	8	416

B. Performance Indicators

As mentioned earlier, five performance indicators were used to evaluate the classification models' performance in diagnosing chronic liver disease. Details of these classifiers are as follows:

TABLE V
CONFUSION MATRIX OF CSVM

	Positive	**Negative**
Positive Diagnose	423	25
Negative Diagnose	30	401

TABLE VI
CONFUSION MATRIX OF QSVM

	Positive	**Negative**
Positive Diagnose	423	18
Negative Diagnose	30	408

- **Accuracy:** To examine the correctly classified subjects in all categories/groups, accuracy is an essential performance indicator. It can be calculated by using Eq. 8.

$$Accuracy = \frac{1}{N}\sum_{i=1}^{N}\frac{TP(i)+TN(i)}{TP(i)+TN(i)+FP(i)+FN(i)} \tag{8}$$

  Here, the number of data groups is denoted with *N*. Even though accuracy is a reasonably strong performance indicator, it can not suffice classifiers' performance evaluation. Therefore, other parameters have also been analyzed to conclude.
- **Precision:** To analyze the performance of the classification model for a particular category, a well-known performance indicator is precision. It can be calculated using Eq. 9.

$$Precision = \frac{1}{N}\sum_{i=1}^{N}\frac{TP(i)}{TP(i)+FP(i)} \tag{9}$$

- **Sensitivity/ TPR:** To indicate the number of times subjects from any specific class (consider class A) have been correctly classified, true positive rate or sensitivity is widely used. Higher sensitivity indicates better performance of a classification model. It can be calculated using Eq.10.

$$Sensitivity = \frac{1}{N}\sum_{i=1}^{N}\frac{TP(i)}{TP(i)+FN(i)} \tag{10}$$

- **Specificity:** It defines the number of samples from other class (class B) is correctly classified. It also gives information about *False Positive Rate (FPR)*, which indicates the number of samples that are classified incorrectly. Both Specificity and FPR can be calculated using Eq. 11.

$$Specificity|(1-FPR) = \frac{1}{N}\sum_{i=1}^{N}\frac{TN(i)}{TN(i)+FP(i)} \tag{11}$$

- **F-Score:** It is also an important performance measure and provides significant information to evaluate the performance of classification models. It highlights the relationship between precision and sensitivity and can be

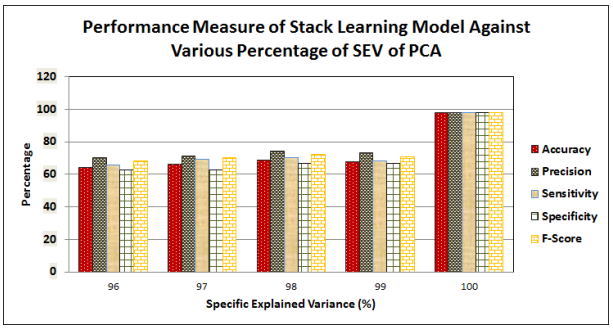

Fig. 4. Performance Measure of Stack Learning Model Against Various Percentage of SEV of PCA

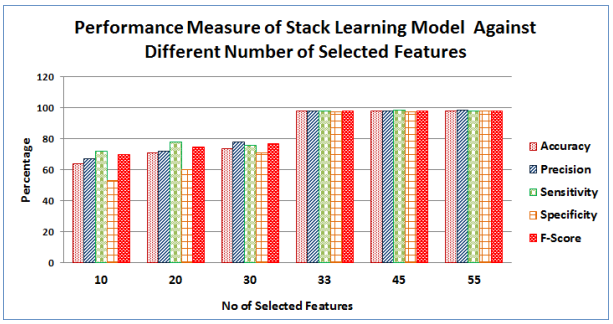

Fig. 5. Performance Measure of Stack Learning Model Against Different Number of Selected Features

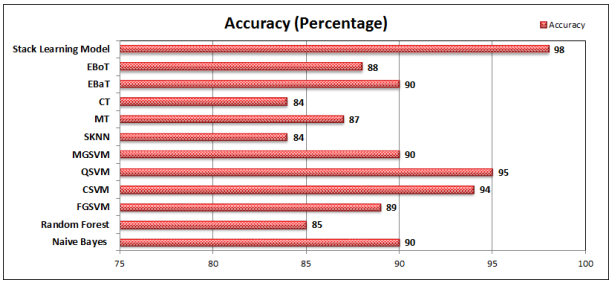

Fig. 6. Accuracy of Classifiers for AI Based Non-invasive Diagnosis of Liver Disease

calculated by using Eq. 12.

$$F - Score = \frac{1}{N}\sum_{i=1}^{N}\frac{TP(i)}{TP(i) + \frac{FP(i)+FN(i)}{2}} \qquad (12)$$

C. Feature Optimization

Data features play a crucial role in accurate classification as misleading data features can disturb the entire classification model. The higher number of data features usually enables classifiers to decide accurately as a higher number of data features make the classes more distinct. However, the higher number of data features increases complexity and computational cost. Therefore, reducing the data feature can optimize the complexity and computational cost but it needs a complete analysis of data features as feature optimization includes the selection of optimal and crucial features and removal of redundant features which are unable to differentiate the classes. In the presented work, two well-known feature selection methods have been incorporated: PCA and Student's t-test. Both methods are discussed and compared in the following subsections:

1) Performance Evaluation with PCA: Classification accuracy of the overall stack learning model was compared against different specific explained variance (SEV) (in percentage). It has been observed that classification accuracy remains the same for different values of SEV and till 99% SEV, there was minor implementation inaccuracy. However, at 100% SEV, a significant change in accuracy was observed. Other performance indicators also followed the same pattern and it is evident in Fig. 4.

Further analysis in terms of the number of features revealed that a total of 49 features combined to reach the 100% SEV of PCA. This is because the performance of dimension reduction or feature reduction techniques varies with the nature, type, and complexity of the data set. While PCA was used to reduce the dimension of data and computational complexity, it has been observed that the performance of PCA was not significant. Hence, it was concluded that PCA was an underperforming feature selection technique for data set under-consideration.

2) Performance Evaluation with Student's t-Test: A detailed analysis was conducted to evaluate the performance of the student's t-test for feature selection. It was observed that there was no significant improvement in the accuracy of all classifiers when operated with the feature vector (FV) of 10 to 30 features. Further, a sharp increase in accuracy was observed with the FV of 33 features. On the other hand, expansion in FV from 35 features produced negligible improvement in accuracy, as shown in Figure 4. It is worth mentioning that apart from accuracy, other performance measures (precision, sensitivity, specificity, F-score) also changed similarly, as shown in Fig. 5. Expansion in FV increases complexity and computation cost. Further, an increase in the number of features from 33 features did not significantly improve accuracy. Hence, the FV of the 33 feature was considered optimal. Here, it is essential to note that the PCA technique used FV of 49 features for the same as discussed in the previous section. Therefore, it was concluded that the student's t-test performed better than PCA.

FV used in this research work included both the iris and physiological features. Iris features, being the dominant features in FV, play a crucial role in the non-invasive diagnosis of liver disease. However, the physiological feature is also vital; hence, to validate the importance of physiological features, the feature selected by the student's -test was analyzed, and it was observed that out of 33 finalized features, FV consists of 8 physiological features. These are Age, BMI, Body Temperature/Fever, Drinking, Heart/Kidney/Lungs Problem, Diastolic Blood Pressure, and Systolic Blood Pressure. This fact further emphasized the importance of physiological features, especially for disease diagnosis.

D. Performance Evaluation of Classifiers

As mentioned before, the overall model of non-invasive diagnosis of chronic liver disease using AI-based ensemble

TABLE VII
OVERALL PERFORMANCE MEASURE OF FIRST LAYER CLASSIFIERS AND META CLASSIFIER (STACK LEARNING MODEL)

Classifier Name	Accuracy	Precision	Sensitivity	Specificity	F-Score
Stack Learning Model	0.98	0.978	0.98	0.977	0.98
CSVM	0.94	0.94	0.93	0.94	0.94
QSVM	0.95	0.96	0.93	0.96	0.95
MGSVM	0.9	0.91	0.89	0.91	0.9
FGSVM	0.89	0.89	0.89	0.88	0.89
CT	0.84	0.85	0.83	0.84	0.84
SKNN	0.84	0.83	0.85	0.82	0.84
MT	0.87	0.87	0.88	0.86	0.87
EBaT	0.9	0.9	0.9	0.899	0.9
EBoT	0.88	0.88	0.88	0.875	0.88
Random Forest	0.85	0.87	0.84	0.86	0.85
Naive Bayes	0.9	0.91	0.88	0.91	0.9

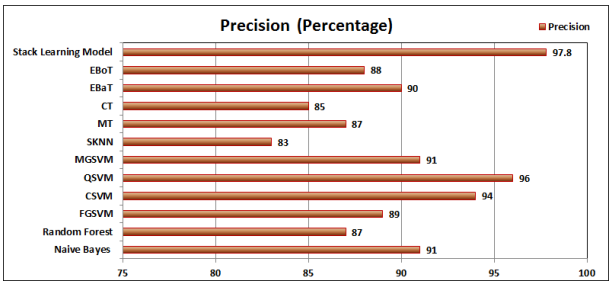

Fig. 7. Precision Comparison of Different Classifiers.

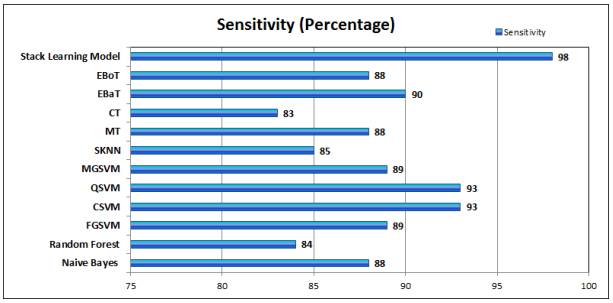

Fig. 8. Sensitivity of Classifiers using Different Machine Learning Algorithms

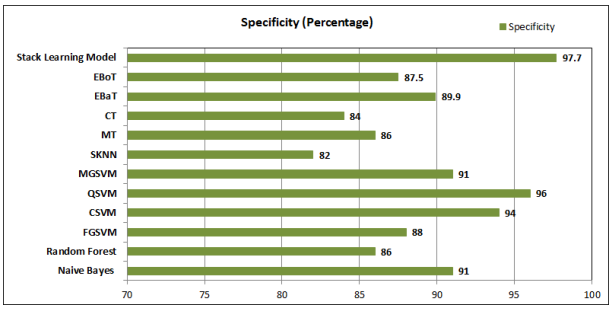

Fig. 9. Specificity of Classifiers for AI Based Non-invasive Diagnosis of Liver Disease

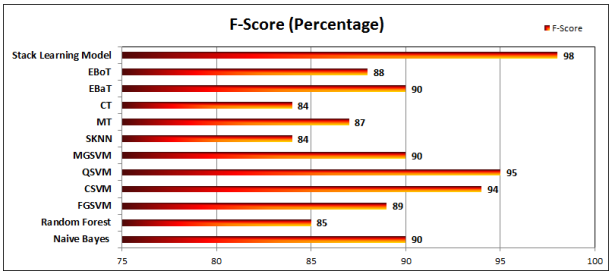

Fig. 10. F-Score Comparison of Different Classifiers.

classification model incorporated eleven different classifiers and combined them using a stack learning technique. However, all eleven classifiers were evaluated individually and at the subsequent stage for comprehensive analysis compared with the stack learning model. Performance of classifiers and stack learning model was evaluated using performance indicators: Accuracy (Fig. 6), Precision (Fig. 7), Sensitivity (Fig. 8), Specificity (Fig. 9), and F-Score (Fig. 10, and the overall result is presented in Table. VII. In layer one, it was observed that individually, classifiers QSVM & CSVM performed significantly well in terms of all performance indicators.

Accuracy and specificity are two essential performance indicators as accuracy defines the ratio of correctly labelled subjects and (1-Specificity) determines the number of subjects incorrectly classified. The higher the specificity lower the false count. It was observed that QSVM outperformed all other classifiers with an accuracy of 95% and specificity of 96%. The second best classifier was ranked CSVM with an accuracy and specificity of 94% as shown in Fig. 6 and Fig. 9, respectively.

The performance of classifiers can also be analyzed by precision and sensitivity. Both the performance indicators highlight the number of correctly classified subjects. Once again, QSVM and CSVM are two classifiers outperforming other classifiers same is evident in Fig. 7 and Fig. 8. F-Score is considered to be a harmonic average of precision and sensitivity. It also highlighted the performance of CSVM and QCSVM as the two best classification models for the non-invasive diagnosis of liver disease, as shown in Fig. 10.

It is once again highlighted that the presented work incorporated the stack learning technique to combine all eleven classifiers to enhance the performance in the diagnosis of liver disease. Therefore, before concluding the results, all performance indicators need to be analyzed, especially for the stack learning model. While designing the overall model, it was anticipated that stack learning techniques would enhance the performance of classification in non-invasive liver disease diagnosis. On analyzing the stack learning model's performance, it was found that stack learning mode; further

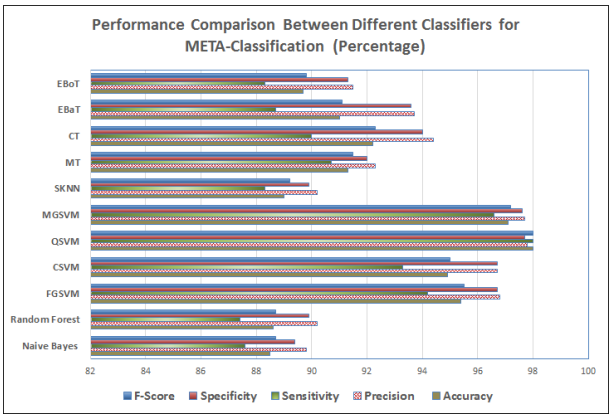

Fig. 11. Performance Comparison Between Different Classifiers for META-Classification

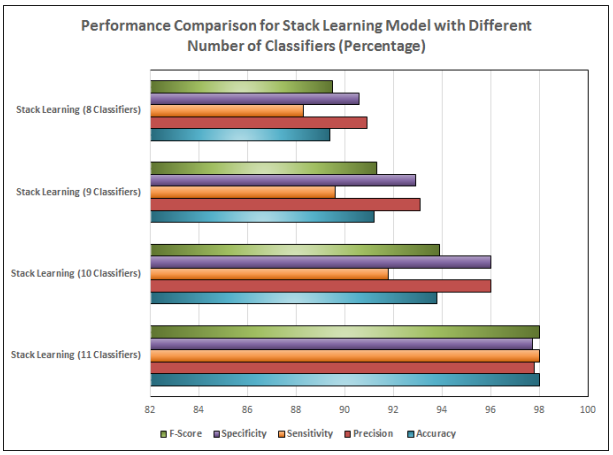

Fig. 12. Performance Comparison for Stack Learning Model with Different Number of Classifiers

enhanced the accuracy from 95% (QSVM) to 98% as shown in Fig. 6. Similarly, precision and sensitivity were improved to 97.6% and 98% as evident in Fig. 7 and Fig. 8.

On the other hand, as previously discussed, specificity is a different performance indicator as (1-specificity) or (100-specificity in percentage) highlights the incorrectly classified subjects. A higher value means fewer incorrect classifications. Once again, the stack learning model presented in this work out-shined and achieved the specificity of 97.7% with the F-score of 98%. It is important to mention that QSVM was selected as a meta-classifier after analyzing all classifiers' performances. Detailed analysis is given in Fig. 11, and it is evident that QSVM outperformed all other classifiers. Further, it was necessary to analyze all classifiers' contributions in the stack learning model and remove such classifiers that are not significant for the overall stack learning model. Hence, the model was analyzed in iterations by removing the classifiers (SKNN, CT, Random Forest) with comparatively worst performance (accuracy) given in Table. VII. It was observed and evident in Fig. 12 that a significant decrease in performance was observed by removing any classifier from the first layer of this presented two-layer classification model. Hence, the presented model of non-invasive diagnosis of chronic liver disease used eleven classifiers combined by stack learning.

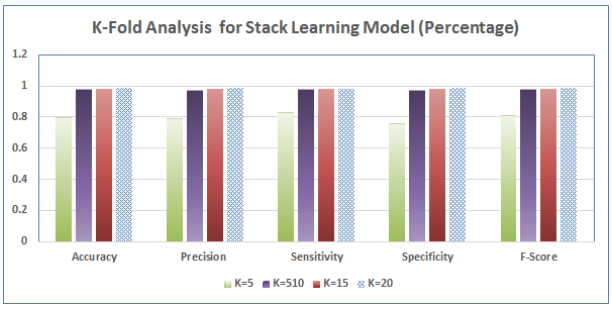

Fig. 13. K-Fold Analysis for Stack Learning Model

As mentioned earlier, 10-fold cross-validation was used to evaluate the results; hence, it is essential to analyze the selection process of 10-fold cross-validation. A detailed K-fold analysis with different K values (5,10,15,20) is given in Fig. 13. It is evident that increasing the value of K above 10 did not produce significant performance improvement; therefore, K=10 was selected for K-fold cross-validation.

At the end of the discussion, it is highlighted that stack learning, an ensemble learning technique of combining eleven classifiers, out-shined the eleven individual classifiers and proved to be a promising model for classification, especially for disease diagnosis.

For further analysis, the presented work was compared with previously published work on the non-invasive diagnosis of diseases linked with the liver. Complete analysis has been presented in a tabular form in Table VIII. The proposed model of AI-based non-invasive diagnosis of OLD has Incorporated a novel approach of combining both the physiological features and IRIS features and showed better performance in terms of accuracy (98%) to diagnose the lung disorder.

E. Advantages & Disadvantages of the Proposed Model

Following are the advantages of presented non-invasive early diagnosis of liver disease:

1) Presented model achieved the highest performance, especially accuracy, specificity, and F-Score.
2) Used eleven different classifiers for comparative analysis.
3) Improved quality of data by using the KNN algorithm for filling the missing values in physiological data.

Limitations of the model are given below:

1) Presented model is limited to diagnosing the chronic liver disease at an early stage and indicates the consultation from a medical practitioner for a detailed diagnosis and type of chronic liver disease.
2) Presented model requires a long training time.
3) Combination of eleven classifiers using stack learning has increased the complexity.
4) Model required a large data-set to achieved the accuracy of 98%. Future work of classification of liver disease will be challenging and need an immense database.

V. Conclusion

A Soft-Computing Approach for Infrared Sensing Based Non-invasive Initial Diagnosis of Chronic Liver Disease Using

TABLE VIII
PERFORMANCE COMPARISON WITH EXISTING WORK

Title & Reference	IRIS or Physiological Features	Classifier	Accuracy (%)
Ksiazek et al. [40]	No	SVM	88.49
Nayak et al. [41]	CT Images	SVM	80
Santos et al. [43]	CHUC	NN	75.5
		LR	73
Brehar et al. [42]	No	Adaboost	72
Sawhney et al [44].	CHUC	FFA	83.5
Abdar et al [49].	NO	Boosted C5.0	93.75
Acharya et al [51].	NO	LDA+SVM+GA	90.3
Presented work	IRIS & Physiological	Stack Learning Model	98
		CSVM	94
		QSVM	95
		MGSVM	90
		FGSVM	89
		CT	84
		SKNN	84
		MT	87
		EBaT	90
		EBoT	88
		Naive Bayes	90
		Random Forest	85

Ensemble Learning has been presented in this paper. Research work was based on a data set of 879 subjects (426 healthy subjects + 453 subjects with chronic liver disease). The given model incorporated a novel approach of combining both the physiological features and iris features for the diagnosis of chronic liver disease. The iris features were extracted from grey-scale images captured using an infrared sensing camera and two well-known feature selection techniques were utilized. Further, the model included eleven different classifiers combined by using the stack learning technique for meta classification. It was analyzed that the presented model is a promising technique as a non-invasive early diagnosis of chronic liver disease, especially for the people of Pakistan with an accuracy of 98 % using student's t-test as feature selection technique and meta classifier (stack learning model). The presented work has a limitation of only diagnosing the chronic liver disease at an early stage and can not diagnose the type of chronic liver disease. However, this limitation can be overcome in the future by identifying the textural and statistical pattern changes of iris images associated with different types of chronic liver disease and acquiring separate data sets for each kind of disease. Furthermore, in the future obstructive lung diseases and kidney-related diseases can also be diagnosed using iris images. Interested researchers can select a specific region (interest of region) for diagnosing other diseases.

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