Employing a Hybrid Convolutional Neural Network and Extreme Learning Machine for Precision Liver Disease Forecasting

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***Abstract*—This paper discusses the critical relevance of precise forecasting in liver disease, as well as the need for early identification and categorization for immediate action and personalized treatment strategies. The paper describes a unique strategy for improving liver disease classification using ultrasound image processing. The recommended technique combines the properties of the Extreme Learning Machine (ELM), Convolutional Neural Network (CNN), along Grey Wolf Optimisation (GWO) to form an integrated model known as CNN-ELM-GWO. The data is provided by Pakistan's Multan Institute of Nuclear Medicine and Radiotherapy, and it is then pre-processed utilizing bilateral and optimal wavelet filtering techniques to increase the dataset's quality. To properly extract significant visual information, feature extraction employs a deep CNN architecture using six convolutional layers, batch normalization, and max-pooling. The ELM serves as a classifier, whereas the CNN is a feature extractor. The GWO algorithm, based on grey wolf searching strategies, refines the CNN and ELM hyperparameters in two stages, progressively boosting the system's classification accuracy. When implemented in Python, CNN-ELM-GWO exceeds traditional machine learning algorithms (MLP, RF, KNN, and NB) in terms of accuracy, precision, recall, and F1-score metrics. The proposed technique achieves an impressive 99.7% accuracy, revealing its potential to significantly enhance the classification of liver disease by employing ultrasound images. The CNN-ELM-GWO technique outperforms conventional approaches in liver disease forecasting by a substantial margin of 27.5%, showing its potential to revolutionize medical imaging and prospects.**

***Keywords*—Liver disease prognosis; convolutional neural network extreme learning machine; grey wolf optimization; patient care**

I. INTRODUCTION

The liver, which is the most significant internal organ in the human body, is essential to many physiological functions. It is situated under the diaphragm in the upper-right region of the abdomen. The liver possesses a special capacity for regeneration and carries out a variety of essential tasks that maintain the body healthy [1]. It has a role in digestion, detoxification, metabolism, and the control of several biochemical procedures. The major functioning cells of the liver are called hepatocytes, and they are responsible for the organ's extensive blood supply [2]. Numerous vital processes that the liver performs are necessary to preserve homeostasis. It handles nutrition from the food people eat, which is one of its main metabolic functions. When glucose is required, the liver releases glucose from storage and manages its production of glycogen for energy. It produces albumin, which aids in maintaining blood pressure and volume, and blood-clotting components [3]. It also processes down lipids into energy or accumulates them as triglycerides through metabolism. In addition, the liver breaks down medications, detoxifies hazardous compounds, and changes ammonia into urea, which the kidneys may then eliminate. Additionally, it is essential to digestion because it produces bile, which facilitates the dissolution of lipids [4].

Hepatitis, Cirrhosis, and non-alcoholic fatty liver disease are among the most common illnesses classified under the category of liver diseases. Hepatitis, which often comes on by viral infections (such as Hepatitis A, B, or C), damages and inflames the liver [5]. The primary feature of cirrhosis is the damage of the liver cells, which is often caused by viral hepatitis, chronic drinking, or other conditions. As the designation implies, non-alcoholic fatty liver disease is characterized by the build-up of fat in liver cells and has the potential for progression [6]. Chronic liver illnesses can lead to the development of liver cancer, particularly hepatocellular carcinoma. Numerous symptoms, such as weariness, jaundice (a yellowing of the skin and eyes), stomach discomfort, black urine, and unexplained weight loss, might be indicative of liver disease. If these medical conditions are not addressed, they might deteriorate and have a significant impact on general health [7]. For instance, cirrhosis can result in liver failure and its complications, which include hepatic encephalopathy and bleeding from oesophageal varices [8]. Liver fibrosis and an increased probability of liver cancer are two outcomes of hepatitis. It's essential to have an early diagnosis and treatment for these illnesses in order to prevent them from becoming fatal. Establishing a healthy routine with a balanced diet, using alcohol in moderation, and receiving a hepatitis virus vaccination are preventive strategies for liver illnesses [9].

In contemporary medicine, the ability to detect liver disorders early and accurately is critical. Liver diseases are a broad category of illnesses [10]. The quality of life and consequences for patients can be significantly improved by immediate treatment and diagnosis. Furthermore, because liver illnesses have a significant negative impact on society and healthcare systems, early detection is a practical and life-saving approach [11]. The application of several cutting-edge technology and data analysis techniques is necessary for predicting liver disorders. In this field of study, machine learning and artificial intelligence approaches have become more popular [12]. A growing number of academics and medical professionals are analysing clinical and patient information utilizing machine learning methods, such as support vector machines, logistic regression, and artificial neural networks, to produce accurate predictions [13]. To determine the probability of liver diseases, these models take into consideration a variety of factors, such as previous medical information, outcomes of blood tests, imaging information, and more. There are significant clinical consequences for accurate liver disease prediction. It makes it possible to create individualized treatment programs and for early intervention [14]. For instance, individuals that are particularly susceptible to liver disease may benefit from attentive observation, lifestyle counselling, and hepatitis virus immunization recommendations. In situations of end-stage liver diseases, early identification can also help ensure a timely liver transplant. Predictive models lessen the overall load on healthcare systems by helping recognize at-risk patients and allocating healthcare resources optimally [15]. By utilizing predictive analytics, healthcare professionals may proactively address the international problem of liver disease.

Current liver disease prediction approaches are unable to fully capitalize on the promise of cutting-edge technology like deep learning and metaheuristic optimization since they frequently rely on conventional machine learning techniques. Conversely, the paper Liver Disease Prediction utilizing Convolutional Extreme Learning Machine offers a novel strategy that gets over the drawbacks of traditional techniques. The research leverages the capabilities of deep learning and non-adjustable hidden nodes by utilizing a hybrid model that includes an ELM for rapid categorization and a CNN for feature extraction. This integration takes advantage of ELM's faster learning rate while also improving prediction accuracy. In addition, by fine-tuning the hyperparameters with GWO, the models become more appropriate for the particular position.

The key contributions of the paper are given as follows:

- The paper presents a unique pre-processing technology for liver disease prediction that combines the capabilities of Combination Wavelet as well as Bilateral Filter. This hybrid technique seeks to efficiently decrease noise and increase significant characteristics in medical pictures or data connected with liver illness, providing a stable platform for additional investigation.
- The research contains innovative feature extraction algorithms that take advantage of Convolutional Neural Networks (CNN) capabilities. By using CNNs' structured and spatial learning abilities, the study improves the extraction of complicated patterns and discriminative characteristics required for effective liver disease categorization.
- For categorization tasks, Extreme Learning Machines (ELM) are used. ELMs are noted for their high efficiency in learning and clarity, making them ideal for dealing with big datasets commonly found in clinical studies. The use of ELM provides an efficient and accurate categorization of liver disease according to extracted characteristics.
- The study uses the Grey Wolf Optimization technique to improve the classification model's accuracy. This optimization strategy, influenced by the social structure of grey wolves, attempts to improve the ELM model's convergence speed and accuracy, hence increasing the overall efficiency and efficacy of the liver disease forecasting system.
- The study assesses the suggested approach for detecting liver illness using important metrics such as precision, sensitivity, accuracy, and the F1 score. It employs 10-fold cross-validation to ensure robustness and gives a thorough grasp of the model's performance in various phases and settings, offering vital insights into its dependability and adaptability in everyday life medical contexts.

The rest of the section is organized as shown below. Section II illustrates literature works on liver disease prediction. Section III gives the Problem Statement. Section IV covers the proposed framework for the liver disease prediction. Section v illustrates the performance measures and summarizes the findings. Section VI provides the conclusion.

II. Related Works

Methods involving machine learning are being used more and more frequently in the modern day in the fields of medical research to identify numerous disorders, such as liver disease. This fatal illness claims a significant number of lives around the world [16]. Early therapy can be beneficial to the patient's recovery if the condition is diagnosed when it is in its early stages. Utilizing supervised machine learning categorization methods to detect liver disease is provided in the study article. In order to recognize the features of liver illness that are most significantly linked together, the study also used a least absolute contraction and selection operator characteristic selection approach on the dataset it had access to. The algorithms' estimations for the illness are evaluated for preciseness, sensitivity, accuracy, and f1-score values using 10-fold cross-validation. With LASSO included, it has been found that the decision tree approach performs optimally. A comparison with contemporary studies is also made to demonstrate the relevance of the suggested system. The possible difficulties of applying the results to various patient demographics or medical environments are not discussed in the research, though. It is critical to recognize the study's relevance to actual clinical practice's limits.

Individuals with chronic liver illness may experience acute-on-chronic liver failure, a clinical condition characterized by sudden hepatic decompensation and a significant short-term death rate. Organ failure, severe generalized inflammation, and a terrible outcome are its defining features [17]. Triaging and prognosticating patients with ACLF is feasible with certain liver-specific prognosis ratings and organ dysfunctions. The purpose of the research is to determine how well artificial neural networks, which functionally resemble biological neural systems, are capable of predicting the mortality associated with liver disease after ninety days. In the study, ANN was assessed in ACLF patients. A significant factor in accurately forecasting patients' short-term mortality is artificial neural networks. Its use with ACLF individuals can be beneficial since it simplifies and automated the process for recognizing individuals who are more likely to die. Artificial neural networks have a great deal of promise to help doctors make decisions, prioritize patients who need liver transplants right away, and forecast death and side effects. Even while the ANN model shows excellent precision, it might not be very interpretable. Understanding the variables that affect forecasts is essential for anyone working in the medical industry. Insufficient interpretability could undermine the model's acceptability and confidence among clinicians [18].

Even with the most recent and advanced equipment, medical professionals still have difficulties in accurately and early predicting liver disease in their patients. In the medical field, support vector machines are extensively utilized. Its effectiveness in generating quality diagnostic variables has been demonstrated. Support vector machine hyperparameter optimization may additionally enhance these outcomes. The suggested approach is predicated on using the crow search technique to optimize support vector machines. With the use of an improved support vector machine classifier, liver illness information from India may be accurately diagnosed. To demonstrate the effectiveness of the suggested method, a comparison with other comparable state-of-the-art algorithms is made. For every metric used for comparison, the efficacy of CSA-SVM is determined to be exceptional when compared to all other techniques. On the other hand, the dataset, code, and repeatability model are not made available in the work. In research related to science, repeatability and transparency are crucial [19].

Accessible medical facilities are essential for individuals in today's world, since healthcare is becoming an increasingly crucial component of daily life. The primary goal of this work is to use feature selection and categorization techniques in software engineering to forecast liver disease. The liver patient's dataset's various characteristics are utilized to forecast the degree of risk for liver disease. The Liver Patients dataset is used to test the accuracy of many methods of categorization. Numerous classifiers outputs are compared, both with and without the utilization of characteristic selection methods. Selection of characteristics and categorization estimation approaches based on software engineering concept are used in the creation of smart liver disease detection software. The article addresses using several categorization algorithms; however, it refrains from going into detail on how these algorithms' hyperparameters were adjusted or improved. Optimizing the parameters of the algorithm is crucial to attaining optimal outcomes [20].

Any condition that has the potential to damage, destroy, or impair the liver's normal function is referred to as liver disease. The death rate from liver illness has increased significantly in the world community. Numerous variables, including human behaviours, awareness problems, inadequate medical care, and delayed discovery, might be responsible for this. Early identification is essential to lower dangers and enhance treatment outcomes in order to address the ever-growing hazards posed by liver disease. As demonstrated in the present research, modern technologies like machine learning might be used to help improve its detection and diagnosis. To help in early identification, evaluation, and lowering of dangers and mortality related to the illness, a more effective approach for timely estimation of liver disease utilizing a hybrid extreme Gradient Boosting algorithm that includes hyperparameter adjustment is presented. The findings showed that the accuracy levels attained by the regression trees and chi-square automated interaction identification and categorization models were significantly higher than the traditional approach. The proposed treatment would help doctors and patients address the issue of liver damage, making sure that instances are identified earlier to avoid cirrhosis and to improve patient survival. The study demonstrated machine learning's assure in the medical field, particularly in the areas of illness monitoring and predictions [21].

The reviews of the literature investigate several machine learning techniques for the diagnosis and prognosis of liver disease. Stressing the value of early diagnosis, they address issues with interpretability and accuracy. Promising outcomes are demonstrated by strategies including CNN-ELM-GWO integration, CSA-SVM optimization, artificial neural networks for acute-on-chronic liver failure, and feature selection in intelligent software engineering applications. Even though these techniques show improved predictive power, there isn't much talk on how to apply these methods to specific demographics, how to interpret models, how to make code transparently available, and how to optimize algorithm parameters. Overall, the research highlights the promise of machine learning in enhancing the identification of liver illness, underscoring the necessity of more development and thorough investigation in clinical settings.

III. Problem Statement

Conventional machine learning algorithms for liver disease prediction have constraints concerning accessibility, transparency, and adaptation to a wide range of patient profiles and medical settings. These models frequently lack the potential to give useful information into ways to make decisions, limiting their use in clinical practice. Furthermore, more robust solutions are required to overcome the difficulties of noise as well as transparency in information from medical imaging [17]. The suggested technique, a hybrid CNN-ELM with GWO optimization, seeks to address these drawbacks. The CNN-ELM hybrid takes use of the capabilities of feature extraction and classification, while GWO optimization refines model hyperparameters. This comprehensive strategy enhances prediction accuracy while simultaneously addressing interpretability and transparency problems. Although the methods used with machine learning seem promising, there are certain obstacles that must be overcome before they can be successfully incorporated into clinical practice. The hybrid method's emphasis on optimizing learning and picture quality makes it a viable solution for obtaining accurate, early diagnosis of liver disease, eventually contributing to better outcomes for patients and lowering the worldwide effect of this life-threatening condition.

Existing methods for forecasting liver disease often rely solely on either CNNs or ELMs, but each approach has its limitations. CNNs excel at extracting hierarchical features from image data but may struggle with non-image data and require large amounts of labeled data for training. On the other hand, ELMs offer fast learning and good generalization but may not capture complex spatial relationships in image data effectively. Thus, there is a need for a hybrid approach that leverages the strengths of both CNNs and ELMs to improve the precision of liver disease forecasting. However, integrating these two disparate techniques poses challenges in terms of model architecture design, feature extraction, and optimization to ensure effective fusion of information from both modalities while mitigating overfitting and computational complexity.

IV. Liver Disease Prediction Using Convolutional Extreme Learning Machine

In the paper, an experimental analysis is conducted to thoroughly investigate the proposed method of employing a hybrid CNN and ELM for precision liver disease forecasting. To begin, a comprehensive dataset comprising a diverse range of liver disease cases, including various imaging modalities such as MRI, CT scans, and ultrasound images, as well as clinical data such as patient demographics, laboratory test results, and medical histories is curated. This dataset serves as the foundation for training, validating, and testing the hybrid model, ensuring that it is representative of real-world scenarios encountered in clinical practice.

Subsequently, the experimental setup is meticulously designed to systematically evaluate the performance of the hybrid CNN-ELM model against baseline methods and individual CNN and ELM models. The dataset is partitioned into training, validation, and testing sets, ensuring proper stratification to maintain the distributional characteristics of the data. The hyperparameters of the CNN and ELM components are then fine-tuned separately before integrating them into the hybrid framework. Throughout the experimentation process, rigorous cross-validation techniques are employed to mitigate potential biases and ensure the robustness of the findings. By systematically varying key experimental factors such as the size of the training dataset, the complexity of the model architecture, and the choice of hyperparameters, insights are gained into the effectiveness and scalability of the proposed method for precision liver disease forecasting. Ultimately, the experimental results provide empirical evidence supporting the utility and efficacy of the hybrid CNN-ELM approach, demonstrating its superiority over existing methods in accurately predicting liver disease outcomes.

This study's approach includes an extensive procedure for predicting liver disease using a dataset of 101 liver ultrasound images. In order to decrease noise and improve the clarity of the images preprocessing is employed using a hybrid technique that combined bilateral filtering and optimum wavelet transformation. Then, in order to extract crucial data from the ultrasound images, a Convolutional Neural Network with six convolutional layers, batch normalization, and max-pooling was created. Using this CNN as the feature extractor, 256 discriminant characteristics were produced for the prediction of liver disease. In order to take use of an Extreme Learning Machine's (ELM) accelerated learning speed and non-adjustable hidden node settings, these characteristics were subsequently introduced into the machine for categorization. By combining the processes of feature extraction and categorization, the hybrid CNN-ELM method improves accuracy. Lastly, to further enhance the effectiveness of the system, the CNN and ELM models' hyperparameters were adjusted using the Grey Wolf Optimization (GWO) technique. This all-encompassing method uses deep learning, metaheuristic optimization and sophisticated image processing to accurately forecast liver disease. The general framework of the proposed method is depicted in Fig. 1.

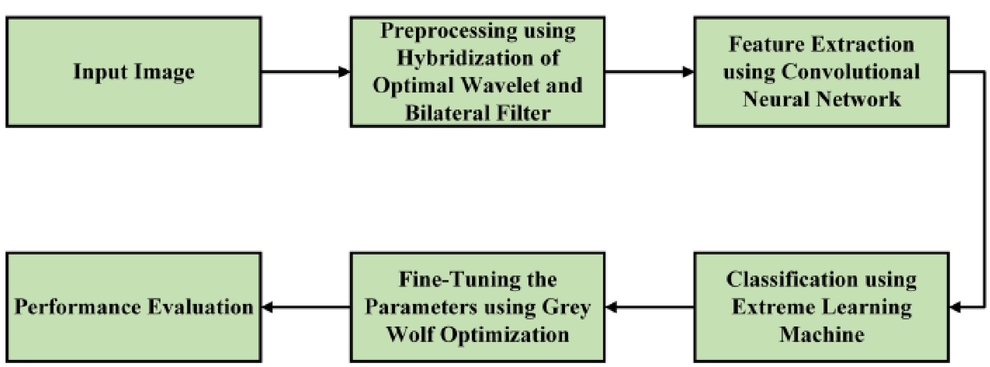

Fig. 1. Overall architecture of the proposed method.

A. Data Collection

There are 101 liver ultrasound images in the collection. Of them, 57 have liver abnormalities such as FLD or heterogeneous liver texture, while 44 images show healthy subjects. A Toshiba Aplio 500 B-mode digital ultrasound scanner was used to obtain all of the images at the Multan Institute of Nuclear Medicine and Radiotherapy, located in Multan, Pakistan. For tissue harmonic imaging, a convex probe was utilized at a frequency of 5 MHz [22]. Each captured image had a resolution of 560 by 450 pixels and was stored as a bitmap file. The medical expert chose 114 64×64-pixel region of interest (ROIs) for categorization into normal and abnormal for these 101 images. These chosen ROIs serve as the basis for all further processing.

B. Hybridization of Optimal Wavelet and Bilateral Filter for Preprocessing

By hybridizing the best wavelet and bilateral filter for sophisticated preprocessing, liver disease prediction can be optimized, improving diagnostic accuracy and dependability. Ultrasound preprocessing is crucial because, in contrast to other imaging modalities like CT and MRI, ultrasound images are more probable to have noise components. Essentially, a speckle noise mostly distorts the ultrasound images. Higher categorization and segmentation accuracy cannot be obtained from a noisy image. For this reason, removing noise from medical ultrasound images is an essential step. For noise reduction in the study, bilateral filters and optimum wavelet hybridization were employed. The input image is first decomposed using the bi-orthogonal 3.7 wavelet transform in the study. After then, it produces four sub-bands, including LL, LH, HL, and HH. It uses the oppositional gravitational search algorithm (OGSA) to ideally acquire the wavelet coefficient in order to enhance the overall appearance of the denoised image. Newton's law of universal gravity and mass interactions serve as the foundation for gravitational search algorithms (GSAs), which are evolutionary heuristic optimization algorithms. To improve the search performance of the GSA algorithm, combining it with an adversarial learning method. Following the decomposition, the bilateral filter is applied to eliminate any noise from the input image. One nonlinear filter that appears to be effective in denoising images is the bilateral filter, which provides spatial averaging without flattening edges. Two Gaussian filters are combined to create this filter. Fig. 2 illustrates the preprocessing procedure.

C. Feature Extraction and Classification Using Convolutional Extreme Learning Machine

1) Feature extraction employing convolutional neural network: Feature extraction is the most critical part of the categorization issue as a model's achievement is based on how effectively the key characteristics from the ultrasound images are retrieved. To enhance the model's effectiveness in categorization, it is imperative to extract the favourable aspects that have enabled discrimination between the two classes. Convolutional Neural Network feature extraction includes employing a deep architecture including convolutional layers to find and highlight relevant patterns and features in data, hence improving analysis and classification. A method for converting higher dimensional information into lower dimensional, useful, and non-redundant information is called feature extraction. It makes it possible to process information more effectively and handle it better. Because the features for these pictures are more complex, a unique deep CNN has been developed to extract 256 significant characteristics for liver disease predictions utilizing the ultrasound images.

Fig. 3 shows the suggested CNN model. The suggested CNN model consists of six convolutional layers, with batch normalization and a max-pooling layer applied after two successive convolutional layers. Because batch normalization re-centres and re-scales the layer inputs, it improves the model's stability and speed of operation. In between two consecutive convolutional layers, there is a pooling layer. The most important elements of the images may be extracted by using max-pooling with 2 × 2 filters, which choose the biggest value from each cluster's whole neuron at the convolutional layers. Since the output is determined through adding the filters to each image tuple, the "SAME" padding has been added to the first two convolutional layers. Because border components frequently include important properties, they have been examined. Zero padding was used in the computation of the border components. The border components, however, were disregarded by the 'VALID' padding.

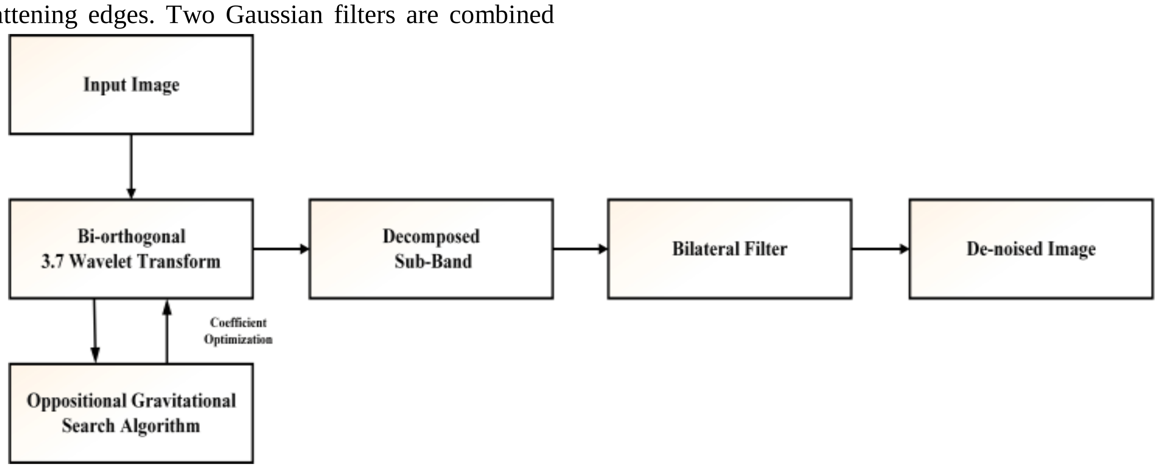

Fig. 2. Process of pre-processing.

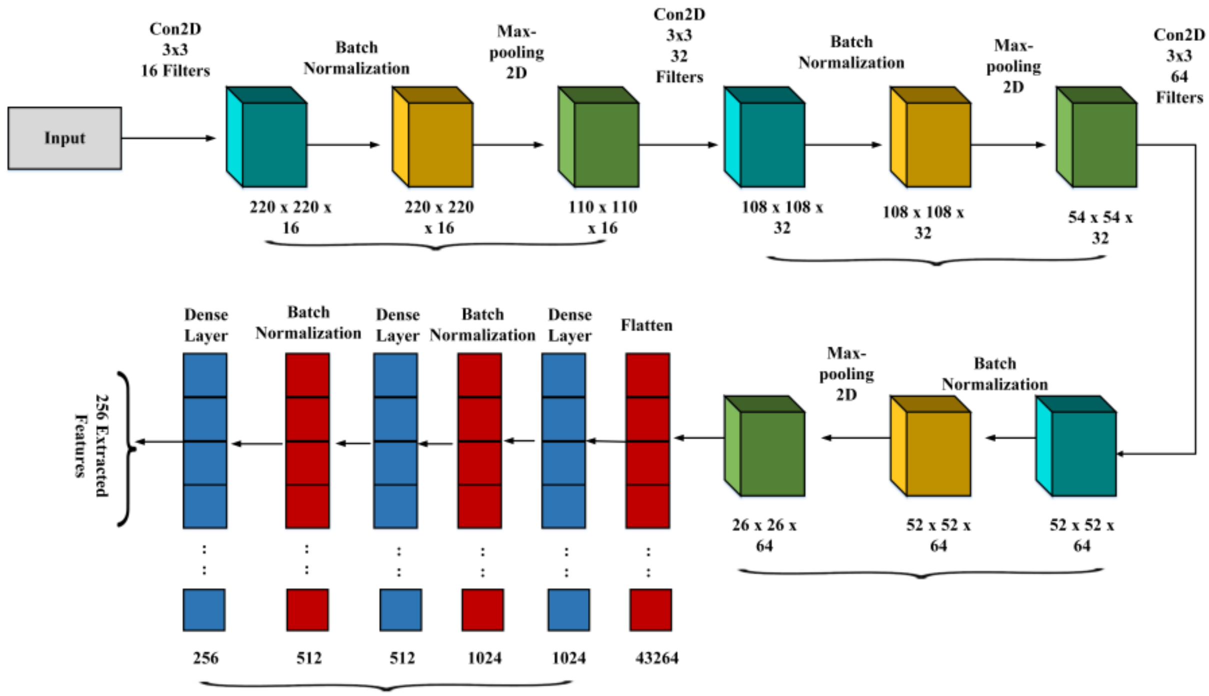

Fig. 3. Proposed CNN model.

ReLU has been used as an activation function in order to prevent the gradient from fading. There are two dropout layers that have been employed, one after the initial fully connected layer and the other after the last max-pooling layer. Both dropout layers have a probability of 0.5. Here, the training time increases significantly by using the dropout layers to reduce overfitting by frequently not training every node in every layer during the training stage. Because the Adam optimizer operates better while training on huge quantities of information and is extremely accurate for CNNs, it has been selected. Lastly, the 512 discriminant characteristics from each picture have been extracted using the final dense layer.

2) Classification using extreme learning machine: A feed-forward neural network with a number of layers of concealed nodes is called an ELM, and is typically used for pattern learning, regression, clustering, small estimate, compression as well, and categorization. It does not require the adjustment of hidden node variables, such as biases and weights. Conversely, the characteristics of hidden nodes can be transmitted down from their ancestors without modification, or they can be assigned at random and never altered. Comparing these models to networks trained using backpropagation, they learn far more quickly. In feed-forward neural networks, the learning process that is most frequently employed is backpropagation, which allows gradients to propagate from the output to the input. Backpropagation, however, has a lot of issues. In most applications, the training procedure takes an extended amount of time since biases and weights must be justified after each iteration. This approach ignores the weight magnitude in order to obtain maximum accuracy, which leads to decreased output over time. The update of weights and biases is no longer a barrier as a result of ELM, a feed-forward network. In order to maximize this model's overall effectiveness, it additionally concentrates on obtaining the lowest weight requirements in addition to the least training error. Simple alternatives are used for addressing the challenge of catching in local minima, hence eliminating such insignificant problems. Fig. 4 shows how ELM functions.

Let S be the arbitrary samples(q_i, r_i), and let $q_i = [q_{i1}, q_{i2}, \dots \dots q_{im}]^R \in P^m$ and $r_i = [r_{i1}, r_{i2}, \dots \dots r_{in}]^R \in P^n$, the standard single- concealed layer feedforward neural networks (SLFNs) with H concealed nodes and an activation function $f\ (\cdot)$ is expressed using Equation (1).

$$\sum_{u=1}^{H} w_u f_u(q_v) = \sum_{u=1}^{H} w_u f(b_u \times q_v + d_u) = o_v, (v = 1,2, \dots\ S) \qquad (1)$$

In this case, $b_i = [a_{i1}, a_{i2}, \dots \dots a_{im}]^R$ and $w_i = [w_{i1}, w_{i2}, \dots \dots w_{im}]^T$ is the weight vector that connects the u^{th} concealed node to the input nodes.d_i is the hidden node threshold, and $o_v = [o_{v1}, o_{v2}, \dots \dots o_{vm}]^R$ is the weight vector connecting the i^{th} concealed node to the output node. R is an example of an SLFN's v^{th} output vector.

Standard SLFNs with H concealed nodes and activation function $f\ (\cdot)$ can estimate these R illustrations with zero error, which means that $\sum_{v=1}^{H} \|o_v - r_v\| = 0$ and that there exist $\omega_u, b_i, and\ d_r$ such that

Using H hidden nodes and an activation function of $f\ (\cdot)$, standard SLFNs can calculate these R representations with zero error. This implies that $\sum_{v=1}^{H} \|o_v - r_v\| = 0$ and that $\omega_u, b_i, and\ d_r$ exist and it is given in Equation (2).

$$\sum_{v=1}^{H} w_u f(b_u \times q_v + d_u) = r_v, (v = 1,2, \dots\ S) \qquad (2)$$

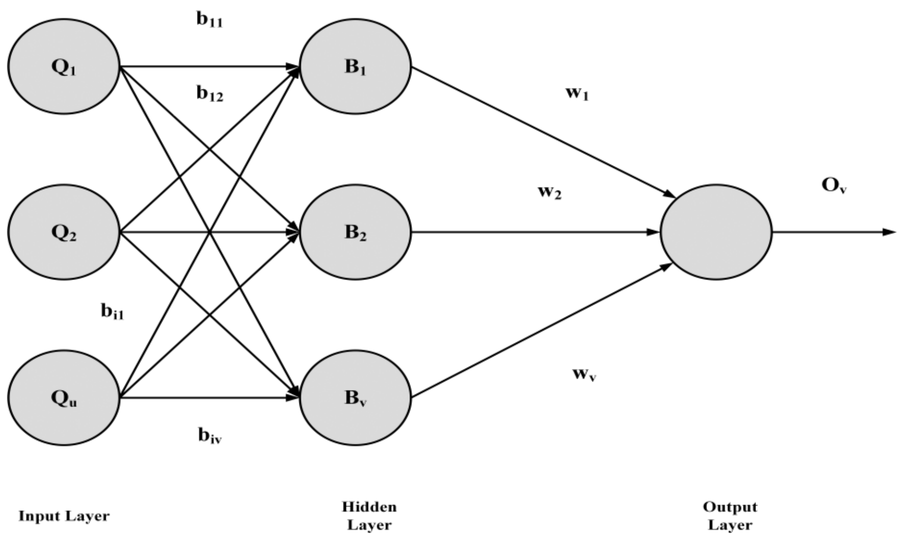

Fig. 4. Working of extreme learning machine

Equation (3), (4), (5) and (6) is an expanded version of the equation mentioned previously.

$$Nw = R \tag{3}$$

Where Equation (4),

$$N(a_1, \dots, a_H, d_1, \dots, d_H, x_1, \dots, x_H) = \begin{bmatrix} f(b_1 \times x_1 + d_1) & \dots & f(b_H \times x_1 + d_H) \\ \vdots & \dots & \vdots \\ f(b_1 \times x_S + d_1) & \dots & f(b_H \times q_S + d_H) \end{bmatrix}_{S \times H} \tag{4}$$

$$w = \begin{bmatrix} w_1^R \\ \vdots \\ . \\ w_M^R \end{bmatrix}_{H \times m} \tag{5}$$

$$R = \begin{bmatrix} r_1^R \\ \vdots \\ . \\ r_M^R \end{bmatrix}_{H \times m} \tag{6}$$

Where, the j^{th} column of N represents the outcome of the j^{th} hidden node based on inputs$x_1, x_2, \dots \dots x_S$, and N is referred to as a matrix of outputs of hidden layer. The linear technique's solution is given in Equation (7).

$$w = N^{-1}R \tag{7}$$

Where, the Moore–Penrose extended inverse of matrix N is denoted by N^{-1}.

Equation (8) defines the ELM's output function.

$$h(x) = q(x)w = q(x)N^{-1}R \tag{8}$$

3) Hybrid CNN-ELM algorithm: The Hybrid CNN-ELM technique combines the strengths of Extreme Learning Machine (ELM) for effective classification and Convolutional Neural Network (CNN) for reliable feature extraction from liver disease-related data. The combination of the CNN-ELM model improves liver disease prediction accuracy by combining CNN's effective visual feature extraction with ELM's fast learning. Its benefits include increased accuracy, faster learning, and more sensitivity, demonstrating efficiency in making exact predictions for liver illness and excellent performance and dependability. By giving a thorough method for identifying relevant characteristics and correctly categorizing liver disease a prerequisite for successful medical intervention this integration improves prognosis accuracy. Fig. 5 below provides a representation of the CNN-ELM hybrid algorithm. CNN and ELM are the two primary designs; CNN was once a characteristic extractor and ELM was a classifier. A single convolutional layer and a single pooling layer constitute the suggested CNN architecture. The study needs one hidden layer for the ELM, which is located between the input and output layers.

The image that reaches the convolutional layer is the first step in the CNN-ELM's main flow. Next, the image matrix that ReLU activates enters the pooling layer. Every processed image matrix then became a one-dimensional vector that could be entered into the ELM's input layer. The neural network uses a generic computation to generate the flattened image information before it enters the ELM concealed layer and is stimulated by the sigmoid function. Following the activation of values, the procedure proceeds to calculate the ELM from the layer that is concealed to the output layer, utilizing the following formula to obtain the categorization outcome, which is Equation (9).

$$W_{s-0} = (Y^R Y)^{-1} Y^R x \tag{9}$$

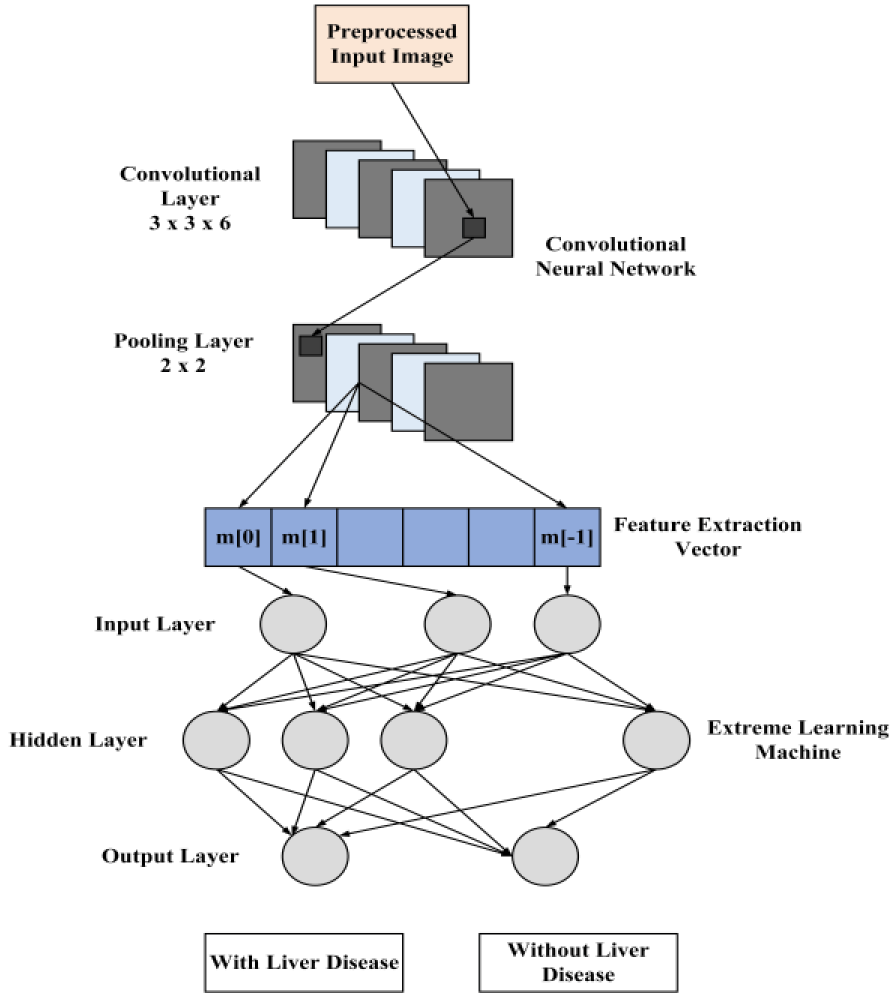

Fig. 5. CNN-ELM hybrid structure.

D. Grey Wolf Optimization Framework for Fine-tuning the Parameters

The Grey Wolf Optimization (GWO) framework optimizes the Convolutional Neural Network (CNN) and Extreme Learning Machine (ELM) components by fine-tuning parameters post-Hybrid CNN-ELM algorithm. Through appropriate parameter modifications in the feature extraction and classification process, the model is gradually enhanced for a better prognosis of liver illness, imitating the hunting behaviours of grey wolves. This iterative technique also improves accuracy. The GWO algorithm mimics the wolf's approach to hunting, which consists of circling the target and working together to make selections. Specifically, GWO is used to improve model hyperparameters including regularization factors, network design, and learning rates when it comes to parameter modifications. Two primary stages comprise the implementation of GWO in this hybrid CNN-ELM architecture. The CNN's architecture and hyperparameters, such as the number of convolutional layers, filter sizes, and learning rates, are first optimized using GWO. This ensures that pertinent characteristics are efficiently extracted from the ultrasound images by the CNN. The ELM model's hyperparameters, including the quantity of hidden nodes, activation functions, and regularization terms, are then adjusted using GWO. Through methodical parameter space exploration and utilizing wolves' cooperative decision-making approach, GWO assists in setting the system's feature extraction (CNN) and categorization (ELM) components, resulting in improved prediction accuracy for diseases of the liver.

GWO, a meta heuristic technique, was proposed [23]. The killing tactic and pack organization of grey wolves had an impact on the technique. Grey wolves live in packs and have an exceptionally hierarchical culture. Decision-making has been handed over to the alphas (α), the wolves' rulers. Alpha wolves are assisted in their tasks by beta (β) wolves, who fall within the following level. The victim in this system is the last individual, known as Omega (ω). If a wolf does not fit into any of the above-mentioned classifications, it is occasionally referred to as a delta (δ) wolf. In line with this well-defined hierarchy, grey wolves try to encircle a food supply, attack, and kill, then search for other prey. The way that wolves hunt is defined as follows: (i) a way to enclose prey; (ii) a way to locate and kill animals; and (iii) a way to battle a prey. Equations (10) and (11) describe how grey wolves circle their prey during a hunting expedition.

$$\vec{K} = \left|\vec{f} \cdot (\overrightarrow{X_w}(n) - \vec{X}(n)\right| \tag{10}$$

$$\vec{X}(n+1) = \overrightarrow{X_w}(n) - \vec{Q} \cdot \vec{K} \quad (11)$$

Where $\vec{X}$ depicts wolf's location in round configuration; $\overrightarrow{X_w}$is the prey's vector position; n is present time; $\vec{Q}$ and $\vec{K}$ are effective vectors that have the following definitions is shown in Equation (12) and (13).

Equations (12) and (13), where $\vec{X}$ represents the wolf's location in a circular configuration, $\overrightarrow{X_w}$ represents the prey's vector position, n denotes the current time, and $\vec{Q}$ and $\vec{K}$ represent effective vectors with the corresponding definitions.

$$\vec{Q} = 2\vec{p} \cdot \overrightarrow{c_1} - \vec{p} \quad (12)$$

$$\vec{f} = 2 \cdot \overrightarrow{c_2} \quad (13)$$

Random vectors equally distributed between 0 and 1 are included in $\overrightarrow{c_1}$ and $\overrightarrow{c_2}$ where the element d is progressively decreased from 2 to 0. The $\alpha, \beta, and\ \delta$ wolves are thought to comprehend it better since the location of the meal is never evident in advance. Equations (14), (15), and (16) are used to determine the victim's location by utilizing the wolves' positions.

$$\vec{K}_\alpha = \left|\vec{f}_1 \cdot \vec{X}_\alpha - \vec{X}\right|,\ \vec{K}_\beta = \left|\vec{f}_2 \cdot \vec{X}_\beta - \vec{X}\right|,\ \vec{K}_\delta = \left|\vec{f}_3 \cdot \vec{X}_\delta - \vec{X}\right| \quad (14)$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{Q}_1 \cdot \vec{X}_\alpha,\ \vec{X}_2 = \vec{X}_\beta - \vec{Q}_2 \cdot \vec{K}_\beta,\ \vec{X}_3 = \vec{X}_\delta - \vec{Q}_3 \cdot \vec{K}_\delta \quad (15)$$

$$\vec{X}(n+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \quad (16)$$

Assuming the study have an estimated position, the next step is to stalk the victim (exploitation). Since the condition of wolves grows closer to the prey's site as p in Equation (11) lowers from 2 to 0, the vector $\vec{Q}$ can be employed to achieve this purpose. Furthermore, variables f and Q both help preserve the method's exploring capabilities intact while eliminating the need for local averages. The variable f can change the location of food and the challenge of foraging, but it can also have an impact on a Q value greater than one, that is, $|Q| > 1$ which forces the wolves to stray from their food and seek it out. After applying the approach to a pack of wolves for a predetermined number of repetitions, Equation (13) will eventually show the location of the prey or the best area in the globe.

Grey Wolf Optimization (GWO) works in collaboration with Extreme Learning Machine (ELM) and Convolutional Neural Network (CNN) to forecast liver illness. GWO refines ELM and CNN hyperparameters by utilizing grey wolf searching algorithms. This two-stage optimization technique gradually increases the model's accuracy. By combining the capabilities of ELM along with CNN and GWO, the unified system of CNN-ELM-GWO obtains improved precision in liver disease categorization. The cooperative approach collaboration of GWO improves the model's resilience, allowing for effective adjustment and optimization, ultimately improving the system's overall effectiveness in forecasting.

V. Results and Discussion

The findings of the suggested method have been addressed in this section. A comprehensive process for predicting liver disease utilizing a collection of liver ultrasound images constitutes a component of the methodology used in this investigation. Preprocessing is done employing a hybrid approach that combines bilateral filtering and optimal wavelet transformation to minimize noise and increase the resolution of the image. Then, a CNN with six convolutional layers, batch normalization, and max pooling was developed in order to obtain important information from the ultrasound images. 256 discriminant features were generated for the prediction of liver disease employing this CNN as the feature extractor. These features were then added to the machine for classification in order to utilize an ELM enhanced learning speed and non-adjustable hidden node settings. The hybrid CNN-ELM technique enhances accuracy by fusing the feature extraction and classification procedures. Finally, the GWO approach was used to modify the hyperparameters of the CNN and ELM models in order to further improve the system's efficacy. This comprehensive approach forecasts liver disease accurately by combining deep learning, metaheuristic optimization and advanced image processing.

A. Performance Evaluation

Evaluation metrics are crucial for evaluating categorization performance. The method that is most frequently used for this is an accuracy measurement. The accuracy of a classifier for a given dataset may be determined by looking at the proportion of testing datasets that it properly classifies. Since selecting the best decisions is not possible simply by using the accuracy measure. Researchers also used a few more criteria to assess the classifier's effectiveness. Metrics including F1-score, accuracy, recall, and precision were utilized to evaluate the efficacy of the suggested approach. The following is a description of each measure's definition:

T_{pos} (True Positive) is used to describe the amount of information that has been effectively categorized.

The term $Fpos$ (False Positive) explains the amount of accurate information that was incorrectly categorized.

False negatives (F_{neg}) are situations where inaccurate information has been categorized as authentic.

The erroneous information values are categorized and referenced to as T_{neg} (True Negative).

1) Accuracy: The classifier's accuracy indicates how frequently it arrives at an appropriate conclusion. The ratio of accurate estimates to all other possible possibilities is known as accuracy. It is demonstrated by Equation (17).

$$Accuracy = \frac{T_{pos}+T_{neg}}{T_{pos}+T_{neg}+F_{pos}+F_{neg}} \quad (17)$$

2) Precision: The precision, or level of accuracy, of a classifier is employed to determine how many results are correctly classified. While lower precision results in many more false positives, higher accuracy reduces the number of false positives. The percentage of instances correctly assigned to all occurrences is known as precision. It is defined by Equation (18).

$$P = \frac{Tpos}{Tpos+Fpos} \quad (18)$$

3) Recall: The recall of a categorization defines its sensitivity, or the amount of pertinent information it produces. The overall amount of $Fneg$ is reduced through recall enhancement. The concept of recall is the ratio of correctly identified cases to the entire number of expected occurrences. This is demonstrable by Equation (19).

$$R = \frac{Tpos}{Tpos+Fneg} \quad (19)$$

4) F1-Score: The F1-Score, which is the weighted mean of recall and accuracy, is the result of combining recall and precision measures. It is characterised by Equation (20).

$$F1\ measure = \frac{2 \times precision \times recall}{precision \times recall} \quad (20)$$

5) ROC Curve: In deep learning and machine learning, area under the ROC curve, or AUC, is a popular assessment statistic for binary categorization issues. The Area under the Curve (AOC) is a visual depiction of the Receiver Operating Characteristic (ROC) curve that shows how effective the binary recognition technique is. In a binary classified issue, the classifier determines whether the incoming data is part of a positive or negative division. The ROC curve displays the $Tpos$ vs. the F_{pos} for different categorization criteria. AOC values are between 0 and 1, where larger values indicate higher effectiveness. An optimum classifier has an AOC of one, whereas a totally randomized classifier has an AOC of 0.5. Since the approach takes into account every conceivable level of identification and provides just one statistic for comparing the effectiveness of various classifiers.

The training and testing accuracy levels of the suggested model throughout several training epochs are shown in Fig. 6. The model performed better and better during the course of 100 epochs of training. The training accuracy was 76.6% and the testing accuracy was 74.5% at the beginning, after only 10 epochs. However, training and testing accuracy levels steadily improved as the model learned and adjusted across additional training epochs. After 100 epochs of training, the model performed admirably, with a testing accuracy of 99.7% and a training accuracy of 99.3% towards the end of the procedure. With the testing accuracy showing the model's ability to produce correct predictions on data that has never been observed before and the training accuracy showing how well the model matches the training information, the graphic illustrates the model's capability to learn and generalize.

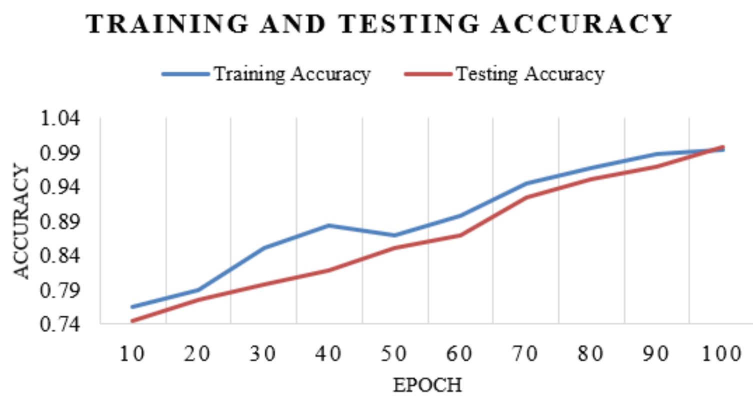

Fig. 6. Training and testing accuracy.

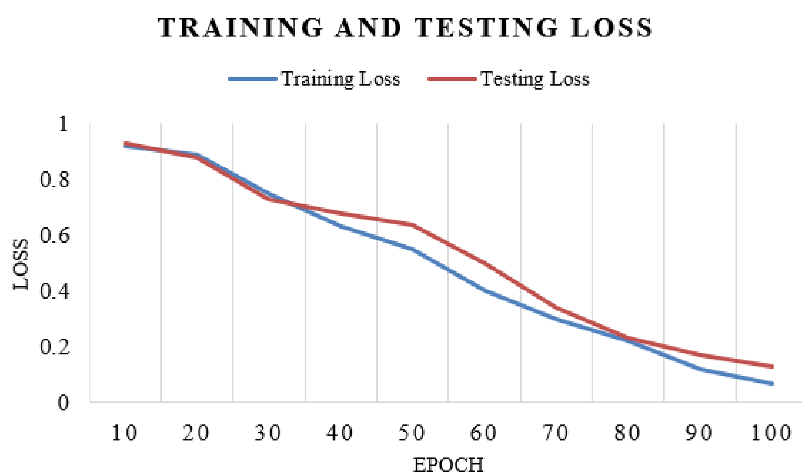

Fig. 7. Training and testing loss.

The suggested model's training and testing loss values are shown in Fig. 7 as it endures several training epochs. It displays the effectiveness of the model and its capacity to reduce mistake. The training loss was very significant at 0.92 at the start of training, with only 10 epochs, suggesting that the model's projections on the training information had a substantial margin of error. Concurrently, the testing loss was additionally slightly elevated at 0.93, indicating that the model did not perform much better on unobserved information. Training and testing losses reduced in an uninterrupted way as the model learned additional epochs, indicating that the model was getting better at generating predictions. The model reached low training and testing loss values of 0.07 and 0.13, respectively, towards the end of the training procedure, which lasted 100 epochs. These low loss values demonstrate the model's capacity to effectively decrease mistakes and generalize, since it has trained to generate extremely precise forecasts on both the training and testing datasets.

In terms of accuracy, precision, recall, and F1-Score for liver disease prediction, Table I and Fig. 8 provide a thorough comparison of the effectiveness of the proposed CNN-ELM-GWO method with other existing approaches, such as MLP (Multi-Layer Perceptron), RF (Random Forest), KNN (K-Nearest Neighbours), and NB (Naive Bayes). The outcomes show that the suggested CNN-ELM-GWO approach performs noticeably better than any other methods.

It demonstrates its capacity to provide incredibly precise forecasts by achieving an amazing accuracy of 99.7%. Additionally, the approach performs very well in terms of accuracy, recall, and F1-Score, all of which are continuously above 99%, indicating its resilience in accurately detecting liver disease cases. The conventional machine learning techniques, on the other hand, show consistently lower performance measures. These include MLP, RF, KNN, and NB. The table highlights the enhanced predictive capability of the suggested CNN-ELM-GWO technique, rendering it an exceptionally efficient and dependable solution for the categorization of liver illness.

The True Positive Rate and False Positive Rate for a binary classification model are shown at different threshold settings in Fig. 9. The fraction of real negative instances that the model mistakenly classifies as positive is represented by the False Positive Rate, which is displayed in the right column. The True Positive Rate shows the percentage of true positive cases that the model properly recognized. The True Positive Rate increases in conjunction with the incremental increase in the threshold from 0 to 0.6 for categorizing occurrences as positive, indicating enhanced sensitivity in accurately identifying positive situations. Concurrently, as the threshold gets more compressed more negative instances are mistakenly categorized as positive, according to the growing False Positive Rate. The relationship between True Positive and False Positive Rates at various categorization thresholds can potentially be evaluated using Fig. 9, which is a useful tool for choosing the best threshold for a particular categorization task.

TABLE I. COMPARISON OF PERFORMANCE OF PROPOSED METHOD WITH OTHER EXISTING APPROACHES

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
KNN [19]	62.90	56.60	55.80	56.19
NB [21]	69.20	70.15	60.16	64.53
MLP [16]	71.59	58.25	70.76	63.89
RF [17]	72.20	62.10	68.80	65.25
Proposed CNN-ELM-GWO	99.7	99.4	99.4	99.2

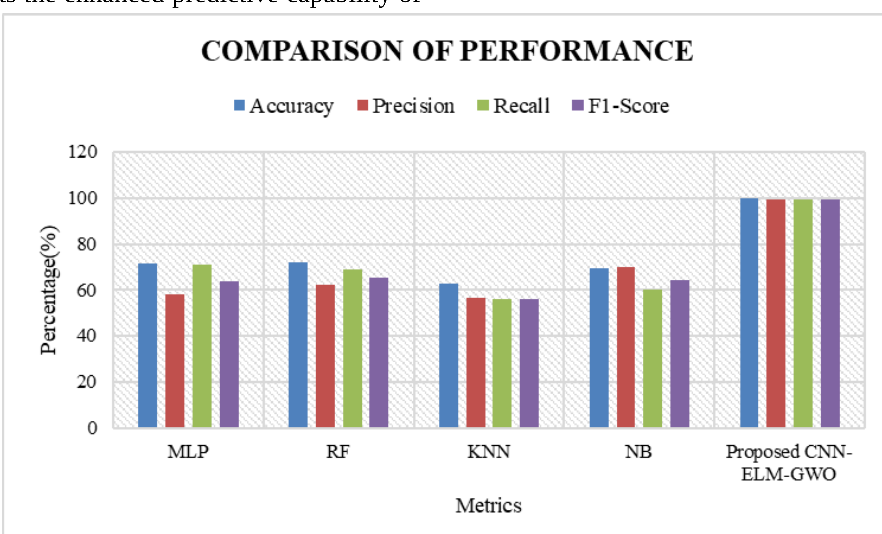

Fig. 8. Comparison of performance of proposed method with other existing approaches.

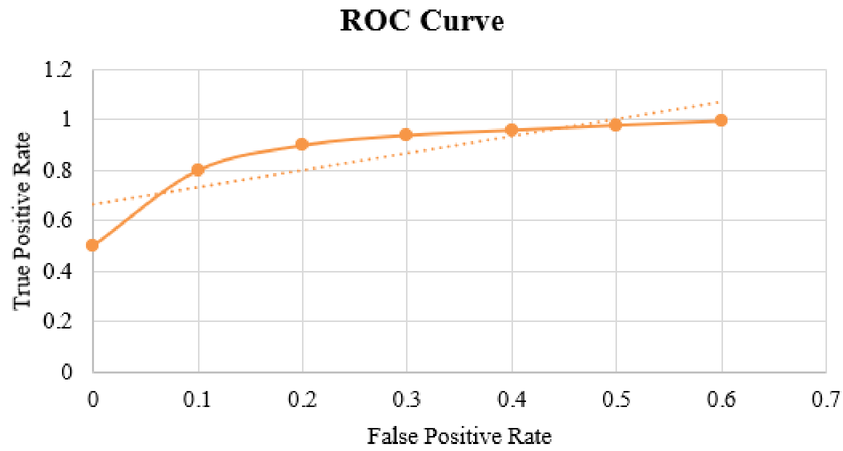

Fig. 9. ROC curve.

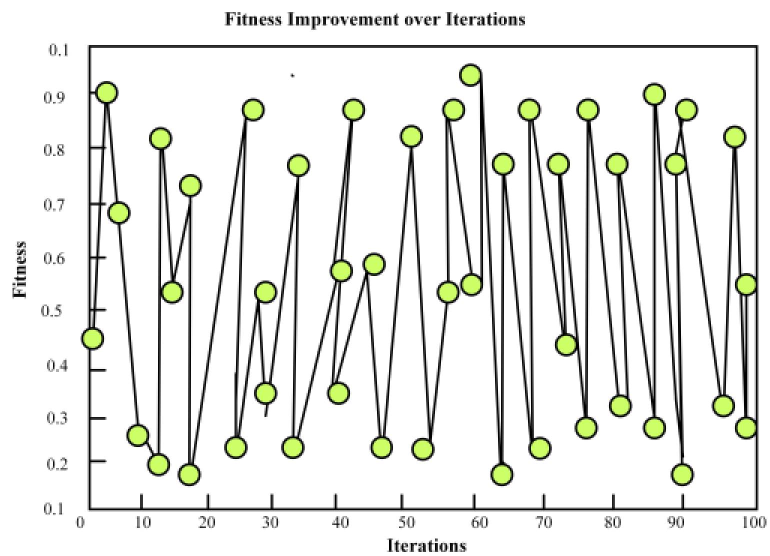

Fig. 10. Fitness improvement over iterations.

The progress of fitness improvement attained by the Grey Wolf Optimization method over several iterations is shown in Fig. 10 shows the Fitness Improvement over Iterations. It serves as an indication for how well the GWO algorithm improves its results over time. The y-axis denotes the fitness level of the algorithm's solutions, which is often a measure of how practically the algorithm's output is to the ideal or intended outcome. The x-axis shows the number of iterations or optimization cycles. The graph's decreasing pattern in fitness values as the iterations go on illustrates that the GWO algorithm is gradually improving and perfecting its solutions. While the decrease in fitness becomes lower in subsequent iterations, it indicates that achieving additional improvements is becoming more difficult.

The high decline in fitness early in the iterations shows that the algorithm is swiftly converging towards better solutions. This graph is crucial for assessing the effectiveness and pace of convergence of the GWO procedure. It also aids in deciding whether to stop the algorithm when the required level of fitness is attained.

A comprehensive evaluation of many datasets, including the Liver Disorder Dataset, Indian Liver Patient Dataset, and the Proposed Liver Ultrasound Images, is shown in Table II and Fig. 11 when compared to important performance metrics, such as accuracy, precision, recall, and F1-Score. The accuracy of the Liver Disorder Dataset was 70%, while the equivalent values for precision, recall, and F1-Score were 68%, 68%, and 69%, respectively. On the other hand, the Indian Liver Patient Dataset performed better, scoring 81% in terms of F1-Score, precision, and recall, and 80% in terms of accuracy. The suggested Liver Ultrasound Images dataset performed significantly superior to the others, with high values for precision, recall, and F1-Score (99.4%, 99.2%, and 99.7%, respectively). In comparison to current datasets, the proposed results demonstrate the higher predictive capabilities of the proposed technique when applied to Liver Ultrasound Images, indicating its potential as a diagnostic tool for liver illness.

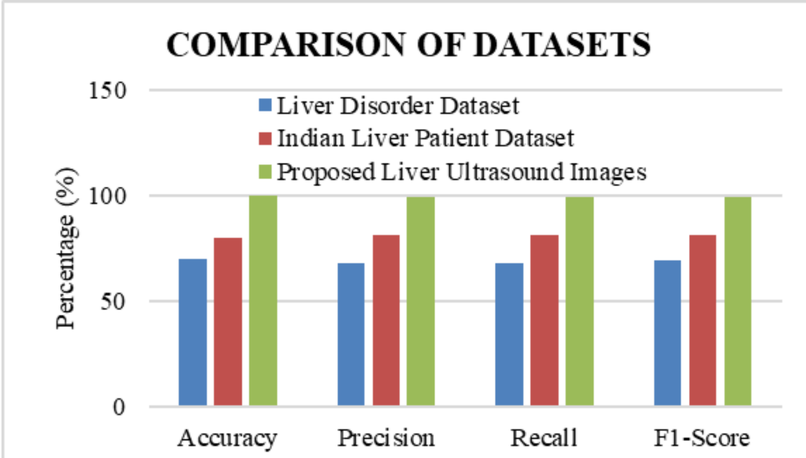

Fig. 11. Comparison of datasets of proposed method with other existing approaches.

TABLE II. COMPARISON OF DATASETS OF PROPOSED METHOD WITH OTHER EXISTING APPROACHES

Datasets	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Liver Disorder Dataset	70	68	68	69
Indian Liver Patient Dataset	80	81	81	81
Proposed Liver Ultrasound Images	99.7	99.4	99.4	99.2

B. Discussion

The suggested liver disease prediction approach uses sophisticated preprocessing, bilateral filtering, and effective wavelet transformation to improve picture quality. When used with an ELM, a six-layer CNN retrieves 256 discriminant features, which optimizes learning. GWO improves the model's efficacy through hyperparameter tweaking. Evaluation measures show remarkable results, with 99.3% along with 99.7% accuracy in testing as well as training, respectively. Traditional constraints in liver disease forecasting include poor accessibility within artificial neural networks, feasible prejudices in dataset depiction, and the difficulty of current time application [20]. The CNN-ELM-GWO method surpasses previous approaches in a comparative analysis, demonstrating its dependability for liver disease categorization. Fitness Improvement across Iterations as well as ROC curve evaluations validate the model's effectiveness and convergence rate. This integrated technique shows potential for reliable liver disease prediction, outperforming alternative approaches. Despite its efficacy, the suggested liver disease prediction approach is limited. The dependence on ultrasound pictures may restrict applicability to other types of imaging. The model's effectiveness may be impacted by the dataset's consistency from a single medical institute. Furthermore, the substantial computational of the CNN-ELM-GWO method may provide difficulties for real-time applications. Further validation on varied datasets, as well as consideration of computing efficiency, are critical to assuring the method's broad application and usefulness. Future research should focus on improving the liver disease forecasting model. Exploring varied datasets collected by various medical institutes will result in greater application. Integrating with additional imaging modalities may increase generalization. Reducing computational complexity will improve real-time application practicality. Investigating interpretability and adding specific patient information might improve customized treatment techniques. Validation in clinical settings, as well as collaboration with healthcare experts, will help to make the model more practical, increasing its influence on liver disease detection and treatment.

VI. CONCLUSION AND FUTURE WORK

This study proposes a unique technique for identifying liver disease based on ultrasound images that takes advantage of the combined abilities of an integrated CNN-ELM-GWO model. The proposed technique surpasses standard machine learning methods with an incredible 99.7% accuracy, emphasizing the critical need for rapid and precise detection of liver disease, which is critical for effective patient treatment. The model provides an effective and innovative architecture by combining an Extreme Learning Machine for classification, a Convolutional Neural Network for feature extraction, and Grey Wolf Optimization for hyperparameter tuning. The CNN-ELM-GWO model's outstanding accuracy emphasizes the need for early detection, which is required for immediate treatment. This result may influence future research that employs advanced algorithms based on machine learning to enhance the identification of various illnesses, advancing the area of medical image evaluation. The findings motivate more research and advocate for more extensive deployment and development of the approach, which ought to result in improved patient outcomes and more informed healthcare decisions. Future research paths might include merging CT or MRI images alongside other types of imaging to increase diagnostic accuracy. Predictions might be made more personalized by using patient-specific information and medical history. The model's practical use would be enhanced if bigger, more diverse datasets were employed for assessment and practical clinical application. Obtaining credibility and adoption of the proposed technique by healthcare professionals necessitates exploring interpretability alternatives for the model's findings. Future research should focus on expanding the dataset to increase model generalization across different populations and medical circumstances. Furthermore, for practical significance, ongoing capability and incorporation into clinical processes must be studied. Improving the CNN-ELM-GWO model's comprehension and removing any biases will assist healthcare professionals in accepting and believing in it.

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