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An effective analysis of the machine learning algorithms for the early diagnosis of Liver Failure

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Abstract: -In the recent years Deep learning algorithms have emerged as a potential means for the diagnosis of medical diseases owing to their capability to extract composite features and patterns from huge datasets. The results of the proposed work demonstrate the efficiency of the Single Layer Perceptron, Multi-Layer Perceptron and auto encoder algorithms through extensive validation in precisely detecting the early signs of liver failure. The efficacy of the algorithms are compared based on performance metrics such as accuracy, F1 score, and recall. The comparative analysis shows that the performance of Multi-Layer Perceptron is superior. The highest accuracy is obtained by MLP as it has True Positive of 1.0, True Negative of 0.975, False Positive of 0.024 and False Negative of 0.0 leading to the accuracy 99.41 and f1 score is obtained as 99.61 and has Precision of 99.23 and Recall of 99.41.

1. Introduction

One of the leading causes of death worldwide is liver failure. When the normal cells in the liver exhibit abnormal activity and appearance, it might result in liver failure. The failure cells then start to destroy nearby healthy tissues and can spread to other parts of the liver as well as to organs that are not part of the liver. The liver, the largest internal organ in the body, filters blood as it circulates throughout the body, transforms nutrients and medications ingested through the digestive tract into chemicals that are ready for use, removes toxins and other chemical waste products from the blood and prepares them for excretion, and controls blood levels of amino acids that are necessary for protein synthesis and blood clotting. Any deterioration in liver health that causes sickness is considered a sign of liver failure. The liver regulates a variety of potentially damaging internal functions, and if it gets sick or is destroyed, the body can suffer severe consequences from the absence of such functions. Any potential problems that can prohibit the liver from performing its intended functions are collectively referred to as "liver failure" in its broadest sense. Normally, the liver must sustain damage to at least three-quarters of its tissue before liver function begins to deteriorate.

The accurate identification of liver failure is essential for successful patient outcomes and therapy. It might be difficult to identify liver failure early since symptoms might not appear until the disease has gone to a serious level. This study investigates the application of deep learning algorithms to the early detection of liver failure. The deep learning programme can find patterns in patient data, including test results, and forecast the possibility of liver failure. [23] Based on the 13 most prominent LFT indicators and the demographic information of the people being screened for liver disease, a densely connected deep neural network (DenseDNN) was created. The dataset, which contained 76,914 samples—more than 100 times as many as the preceding datasets—was utilised to test the method. Area under Curve (AUC) values for DenseDNN are 0.8919, DNN 0.8867, Random Forest 0.8790, and Logistic Regression 0.7974. Deep learning models perform much better than traditional approaches.

The dataset includes patients with malignant and benign liver tumors confirmed through biopsy or surgical specimens, and benign cases with follow-up for over a year. In the training process of liver

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failure diagnosis using the MKL-NHSVM+ model, features are manually extracted from a BUS image and its corresponding three CEUS images, which are then inputted to the model for training. The BUS image is the diagnostic modality, and the three CEUS images contribute to the training. The Existing system in spite of its feasibility, if the training data is not a part of target population the performance suffers. It increases the computational complexity and training time and no comparison of other algorithm is done for evaluating best model.

Significance of the proposed system:

Deep learning algorithms are used to train data to more thoroughly understand the features. The development of a classification model is based on the learning and performance comparison of the chosen algorithms utilizing their performance measures. Finally, a GUI is created utilizing the flask framework to implement the model of choice, allowing the patient to enter the necessary information to determine the condition of his or her liver.

Major Contribution:

- It can adapt to new data and changing environments where data changes over time.
- Can identify subtle changes in patient data that may not be clear to human observers.
- Can analyze large datasets quickly, enabling faster diagnoses of acute liver failure.
- Deployment can also be done in desktop application.

2. Related Work

Deep learning algorithms [1] are employed to detect disorders early on. In the paper named A Robust Deep Learning based Framework for High-Precision Detection of Liver Disease (LSTM), three techniques were employed: Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Long Short-Term Memory. The effectiveness of various approaches was evaluated using a variety of measurement techniques, including accuracy, precision, recall, f-1 score, false positive rate, false negative rate, mean error, etc. [2]A novel method to automatically estimate NAS score and fibrosis stage from CT data that is non-invasive and more affordable than liver biopsy. A method is offered to merge the information from CT and H&E stained pathology data when both types of data are available in order to improve the performance of NAS score and fibrosis stage prediction. For pathologists using computer-

assisted diagnosis, this is very helpful. The proposed research of Learning in Liver Biopsies using Convolutional Neural Networks [3] provides a fully automated diagnosis tool due to the great discrimination capacity of histological findings in liver biopsy pictures. The recommended methodology, based on deep supervised learning and image processing techniques, has been used to determine effective convolutional neural network (CNN) architecture.

One of the most important organs in the human body is the liver. [4]There are several liver problems that require prompt medical attention. Early diagnosis and patient care are crucial to lowering the risk. Different Machine Learning (ML) models can help the healthcare sector predict diseases at an early stage. The goal of the study is to anticipate liver sickness using a variety of ML models applied to the Indian Liver Patient Dataset (ILPD). Several Ensemble Learning (EL) models, including Support Vector Machine (SVM), K-Nearest Neighbour (KNN), Random Forest (RF), Artificial Neural Network (ANN), and others, were used in this study.

[5] The liver's main job is to get rid of waste produced by living things. This is a very dangerous illness, so the first thing that has to be done is to reduce the likelihood that this fatal illness will spread. Early discovery can also help save the organism. There have been numerous improvements made in illness prediction using machine learning classification algorithms as KNN, random forest SVM, and logistic regression. To tackle this issue, further deep learning techniques including artificial neural networks and convolution neural networks are also used. Because the first stage's symptoms are so minimal, it is very difficult to diagnose liver disease early on. [6]The traditional procedures incorporate lab data and physical examinations. This research intends to illustrate a diagnosis for patients with liver disease prediction utilizing combined machine learning models. Doctors utilize Artificial Neural Networks (ANN), Decision Trees, and K-Nearest Neighbors (KNN), three machine learning methods that have been optimized, to diagnose liver disease accurately. Given data is classified and outcomes are generated with the aid of these algorithms.

[7]The proposed system uses an intelligent system based on logical inference and a generalized regression neural network. An expert system based on logical inference is used to assess whether a patient may have Hepatitis B or another kind of

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hepatitis. Next, utilizing artificial neural networks, the hepatitis B predictions will be created. In order to analyze hepatitis data and forecast the severity of a patient's hepatitis B illness, researchers employ the Generalized Regression Neural Network. The findings show that generalized regression neural networks may reliably detect hepatitis B. [8] The Indian liver patient records dataset, the Hepatitis C dataset, and the Cirrhosis Prediction dataset are the three datasets from which the liver disease features were extracted. The POA-modified MRCNN model is primarily used to determine how various laboratory measurements and diagnoses are related to one another. The suggested model is contrasted with other cutting-edge techniques including Opposition-based Laplacian Equilibrium Optimizer, Adaptive Hybridized Deep CNN, SVM, and Tree-based classifiers in terms of Accuracy, Precision, Recall, F-measure, and Mathews Correlation Coefficient (MCC).

[9]In Deep Learning Techniques for Fatty Liver Using Multi- View Ultrasound Images Scanned by Different Scanners: Development and Validation Study, the model trained on CLKL images achieved 80.1% accuracy, 86.2% precision, and 80.5% specificity to diagnose fatty liver disease. According to regression analysis, there was a moderate degree of approximation between the projected fat fraction values and the MRI-PDFF values, with an $R2$ of 0.633.

[10]The other suggested study consists of a variety of elements, including deep neural networks and Spearman's rank correlation. The 52 features, comprising the gradient co- occurrence matrix (GLGCM) texture features and the grey level co-occurrence matrix (GLCM) texture features, are used for classification and prediction. the deep neural network's prediction and classification capabilities (DNN). On the basis of the various features, the various classifications are conducted. Spearman's rank correlation was used to predict the rank correlation utilizing the different DNN network layers. The experiment in the proposed study is performed on MRI datasets and pictures. The predicted dataset is rated using sensitivity, specificity, accuracy, and precision. As compared to the currently preferred approaches, the anticipated findings show enhanced results in terms of comparative parameters.

Machine learning technology [11] has made it feasible to predict liver disease in its early stages. By creating innovative methods to implement early disease prediction systems even in a remote place,

this technology significantly benefits the healthcare industry. The implementation of liver disease detection makes use of SVM, KNN, K-Mean clustering, neural networks, decision trees, and other machine learning algorithms to provide variable degrees of accuracy, precision, and sensitivity. Using an ANN algorithm [12], a different model for liver problem requests that separates the patient's useful data. Whether there is a possible cause for the disorder or not, the remedial records are organized. This suggested methodology classifies the collected features using M-PSO and ANN. When compared to current request computations differently, the ANN methodology increases accuracy.

[13]CNN proved successful in categorizing liver disorders, with accuracy rates of 75.55% and 72.00% on the BUPA and ILPD datasets, respectively, according to experimental results of Deep Learning for Liver Disease Prediction. [14]In developing countries, diagnosing liver disease is a significant medical difficulty. Around 30 billion people worldwide have liver failure every year, which ultimately leads to death. Previous algorithms for detecting liver abnormalities have higher theory of constraints metrics and lower accuracy. Advanced, efficient, and effective liver disease detection is necessary because the lesion on the liver couldn't be diagnosed properly with earlier models. This method suggests a deep liver anomaly detection method based on Dense Net convolutional neural network (CNN) to get beyond the shortcomings of existing models. A system of deep neural networks has been effectively used to forecast the disease using a dataset. Hepatitis has alternating symptoms, making prediction a difficult task. By using a Deep Neural Network model, the aim of this effort is to precisely and reliably anticipate the disease [15].

[16] Eliminating waste created by living organisms is the liver's primary function. Since this is a highly severe sickness, the first thing that needs to be done is to lessen the possibility that it will spread and become fatal. The organism may be saved if it is discovered early. There have been numerous improvements made in illness prediction using machine learning classification algorithms as KNN, random forest SVM, and logistic regression. To tackle this issue, further deep learning techniques including artificial neural networks and convolution neural networks are also used.

Steatosis [17] increases the risk of developing hepatocellular carcinoma (HCC). The healthcare

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sector has recently given more priority to stopping the spread of these illnesses. The computed tomography used to provide microscopic biopsy pictures is regarded to be the norm in contemporary medical research. By creating a convolutional neural network (CNN) and contrasting its detection performance with that of other pre-trained deep CNN designs, the project being presented intends to establish good generalization capabilities of four histological liver characteristics.

Early identification is essential for minimizing the possible harm that could be done by this devastating disease. [18]Infected people make up roughly 3.5% of the population worldwide. Disease prediction is progressing significantly with the use of machine learning (ML) classification methods like K-nearest neighbors (KNN), Random Forest Support vector machine (RFSVM), and logistic regression. Two examples of deep learning methods applied to this problem are artificial neural networks and convolutional neural networks. Patients with this illness will have a far greater chance of living longer and avoiding chronic liver disease (CLD) if they use these methods.

Convolution Neural Network (CNN)[19] is based on the CNN-LSTM-CFS model, which combines long short-term memory (LSTM) with correlated feature set to produce an automated technique for determining the stage of liver tumors. Correlated features from a labelled feature set are used in the suggested method. The most crucial imaging requirements for each class seemed to be represented by features that were relevant, and feature maps have in fact been consistent with the original image characteristics. To provide an appropriate diagnosis and treatment plan, the distinction between malignant and non-cancerous lesions must be made in addition to the CT-based lesion-stage description. There is a need for very high levels of knowledge, resources, and past experience. Abdominal CT scans of the liver can be used to distinguish between benign cysts and colorectal cancer metastases using a deep end-to-end learning technique. When the results of the existing methods and the new model are compared, the results demonstrate that the proposed model outperforms traditional methods. One-dimensional convolutional neural network [20] was used to build a deep-learning model that was tuned to distinguish between individuals with cirrhosis and those who are healthy controls (CNN). The highest peaks were identified (using the test dataset's average SHAP profiles). Distinct, visible peaks that were

connected to prediction were explained by Shapley Additive Explanations. CNNs demonstrate the capability to predict the existence of cirrhosis using a comprehensive volatolomics profile of patient breath samples.

The most relevant imaging criteria for each class appear to be features, and feature maps have been consistent with the voxel properties of the original picture. This deep learning system illustrates the idea of highlighting particular stages of the decision-making process of a pre-trained deep neural network by an examination of the inner layers and a description of the traits that produce predictions[21]. A binary classifier based on GoogleLeNet (Inception-V1)[22] is used in one of the studies to categorize photos of HCC histology. The classifier classified HCC with 92.16% (4.93) sensitivity and 90.57% (2.54) specificity. Although there is evidence that the amount of training data is positively connected with the classification accuracy of deep learning, it is frequently unclear how much training data is necessary for deep learning to function satisfactorily in clinical diagnosis.

3. Methodology

The suggested approach is a deep learning model that is built using a dataset of liver failure data in CSV format. The dataset features and target column are first determined using our domain expertise in the field of healthcare.

Data Preprocessing and Validation: The data to train the model is provided as the input to this phase. Collecting knowledge about current activity recognition systems and their advantages and disadvantages are the main tasks of preprocessing the data. The liver patient dataset is loaded into a Pandas Data Frame using the read_csv() function. To get an idea of the size of the dataset, the shape and size functions are used. The info() function is used to check the data type and information about the dataset. The describe() function is used to describe the statistics of the dataset. The sum of the duplicated records is calculated using the duplicated().sum() function. The duplicated records are then removed using the drop_duplicates() function. The number of duplicates is checked again to make sure that all duplicates have been removed. The sum of the missing values is calculated using the isnull().sum() function. The missing values are removed using the dropna() function. The name of a feature/column in the dataset is changed using the

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rename() function. The unique values of some features/columns are checked using the unique() function. Basic statistics of some features/columns are calculated using the describe() function. The corr() function is used to calculate the correlation between the features/columns. The Categorical() function is used to describe the categorical variables in the dataset. The LabelEncoder class from the scikit-learn library converts categorical data into numerical labels that can be used as input for deep learning algorithms.

Development of User Interface: The user interface is designed using Flask. Developing the user interface for liver failure diagnosis system involves using HTML, CSS, Bootstrap with Flask framework. The home page gets displayed when the user visits the website. This page contains a form that allows the user to input values for certain liver disease features, such as age, gender, total bilirubin, direct bilirubin, and so on. The predict button is called when the user submits the form. This page retrieves the input data from the form, converts it into a numpy array and passes it to the pre-trained machine learning model. The model then predicts whether the user is affected or not affected by liver disease, based on the input data. The predicted output is then displayed on the home page, letting the user know whether they are affected or not.

Data Visualization: The data from 583 liver patients were examined in this study using 416 samples from liver patients and 167 samples from non-liver patients. After the data pre-processing and data validation process, the data is used for visualization. Using Python's matplotlib library, a bar graph is plotted for the liver patients who are affected and not affected. The ratio of all liver patients who are affected and not affected is shown in Figure 1
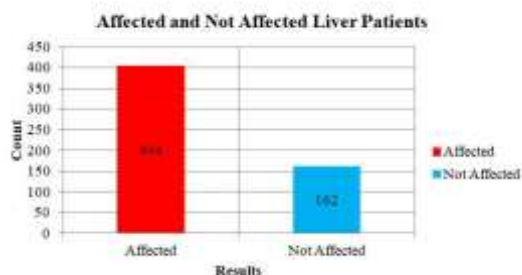

Figure 1.Statistics of liver patients

In addition, from the dataset of liver patients in 441 male samples and 112 female samples were taken for analysis. Using Python's matplotlib library, a bargraph is plotted for the affected liver patients for

male and female gender. The ratio of all affected liver patients between the male and female gender is shown in Figure 2
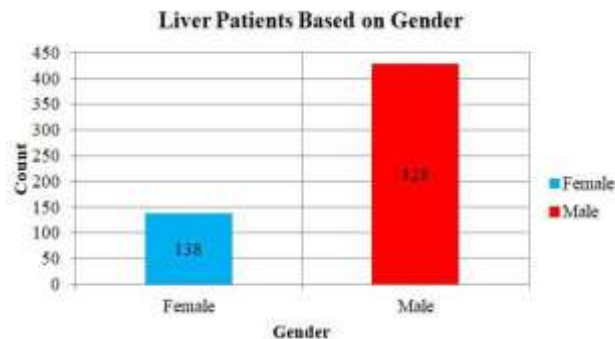

Figure 2. Statistics of the gender split of liver patients

Integration of the trained model with Flask: The system that diagnosis the patient's liver condition and predict based on the best trained model is integrated to form the system for accurate prediction, and deployed in real-time to effectively diagnosis the liver condition in patients. Integration is accomplished with the utilization of different deep learning algorithms like MLP, SLP and auto encoders to predict the result with the same dataset and choose the best algorithm that yields the best accuracy.

SYSTEM ARCHITECTURE

The liver's job is to filter the blood that the body circulates, transforming the medications and nutrients that are ingested into chemicals that are ready for use. Other crucial tasks carried out by the liver include clearing poisons and other chemical waste products from the blood and preparing them for excretion. Your liver's cells are where liver failure starts. In the modern healthcare system, deep learning is used to improve the likelihood of early disease prediction. Data is the key thing artificial intelligence needs. The architecture shown in Figue 3.
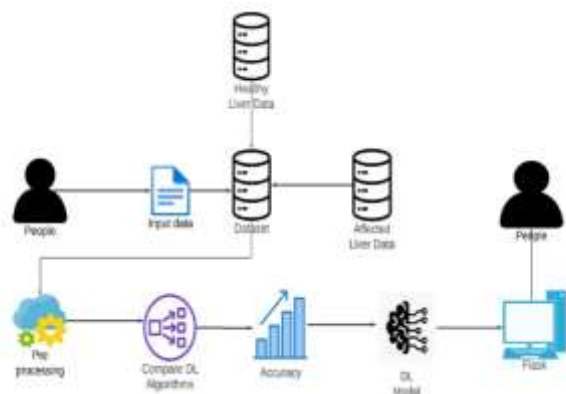
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Figure 3.Sytem Architecture

Construction of a Predicting Model

Deep learning needs data gathering which requires a lot of past datasets. Before data pre-processing, raw data can't be used directly so raw data has to be preprocessed and then different deep learning algorithms like Multilayer Perceptron (MLP), Single layer Perceptron (SLP) and Autoencoders are used to compare by using performance metrics. This model functions properly and provides accurate predictions while being trained and tested. On the basis of the correctness of the test results, the test set is predicted using the data model that was developed using deep learning algorithms shown in Figure 4. The following factors contribute to the effectiveness of DL algorithms prediction models:

It delivers superior outcomes for classification-related issues.

Preprocessing can be used to efficiently remove outliers, irrelevant variables, and mixtures of continuous, categorical, and discrete variables.

It produces out of bag estimate inaccuracy, which has been demonstrated to be impartial in
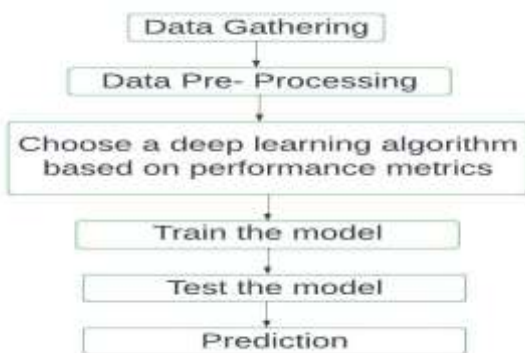several studies and is quite easy to correct.

Figure 4.Predicting Model Diagram

Multilayer Perceptron (MLP): The first layer in MLP is the input layer, which takes the raw input data (such as an image or text) and feeds it forward to the next layer. The next layers, called hidden layers, perform a series of nonlinear transformations on the input data to learn complex patterns and relationships between the input features. The final layer, called the output layer, produces the prediction or classification output based on the learned patterns in the previous layers.

Backpropagation is a technique used during MLP training to update the weights and biases of the neurons in each layer to reduce the discrepancy between the projected output and the actual output. The network is given labelled input and output data during training and the weights are adjusted to minimize the difference between the expected and actual output. Unless the error is minimized or a predetermined stopping threshold is satisfied, this procedure is repeated across a number of epochs.

In this work, the MLP has two hidden layers, each with 10 neurons. The maximum number of iterations the solver should perform is set to 1000. The random state is set to 42, which ensures that the MLP will be initialized with the same random weights each run time. This can be useful suited to large datasets and deep neural networks. The performance Metrics for Multilayer Perceptron as shown in Figure 5.

Single Layer Perceptron (SLP): The input layer takes in signals or characteristics from a dataset or the outside world. The inputs are given to the perceptron, which multiplies each input by the appropriate weight, adds the weighted inputs and then applies an activation function to the outcome. The perceptron's output is the activation function's output.

The activation function of SLP is a threshold function, also known as the Heaviside step function, which outputs 1 and 0 respectively. The perceptron's parameters, weights and bias, are discovered throughout the training phase.

Presenting the input patterns to the perceptron and modifying the weights and bias depending on the discrepancy between the actual output and the desired output constitute the SLP training process. A cost function, such as mean squared error (MSE) or cross-entropy loss, is used to determine the error. A learning rule such as the delta rule or perceptron learning rule is used to update the weights and bias. In this work, the SLP contains a single neuron in a dense layer that receives 11 inputs (input dim=11) and uses a linear activation function. Adam is the optimizer used for training, while mean square error is the loss function. The fit() function is used to train the model, with the parameters X train and Y train

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serving as input data and target labels, respectively. With a batch size of 32 and verbose set to 0, the training is carried out across 100 epochs without printing progress updates to the console.

The encoder network converts the input data into a lower-dimensional representation known as a latent coding or embedding that encapsulates the key characteristics of the input data.

The bottleneck layer is a layer in the encoder network that has a lower dimension than the input layer and the output layer.

The input data must be compressed into a lower-dimensional representation by the bottleneck layer. The decoder network, which is likewise a deep neural network with numerous layers is then given the compressed representation. The decoder network reconstructs the original input data by mapping the compressed representation back into the original input space.

The autoencoder is taught to lessen the discrepancy between the original input and the reconstructed output. To do this, a reconstruction loss function is constructed, and it measures the difference between the original input and the rebuilt output. The autoencoder adjusts the neural network weights by back propagating the reconstruction loss from the output layer to the input layer during training. The weights are updated using an optimization strategy to minimize reconstruction loss.

After the autoencoder is trained, it can be used for various tasks such as data compression and feature extraction. The quality of the autoencoder is evaluated by measuring its reconstruction error on a validation set of data that the model has not seen during training. The performance Metrics for Single layer Perceptron as shown in Figure 6.

Autoencoders: The input to the autoencoders is a dataset consisting of examples of the type of data that the model is designed to work with. This can be images, audio, text or any other type of data. The encoder network which is generally a deep neural network with numerous layers receives the input data. The performance Metrics for Autoencoders as shown in Figure 7.

4. Results and Discussion
Performance Metrics
To evaluate the performance of the proposed method confusion matrix, precision, accuracy, f1 score and recall are utilized. These are not only efficient tools for performance evaluation but also helpful in calculating various other performance

metrics shown in Table 1.

Precision: The positive predictive value (PPV), also known as the ratio of true positive (TP) components to the sum of TP and false positive (FP) components, can be calculated using the equation. This ratio is an important performance metric for detection.

$$Precision = TP/ TP + FP$$

Recall: The true positive rate, also known as sensitivity value, is the ratio of true positive (TP) components to the sum of TP and false negative (FN) components. This ratio can be calculated using the equation and is an essential performance metric for detection.

$$Recall = TP/ TP + FN$$

F1 Score: The calculation of the F1 score, an important performance metric in information retrieval, involves using a mathematical expression that is the harmonic mean of both recall and precision.

$$F1 - Score = 2 \times Precision \times Recall /Precision + Recall$$

Accuracy: The accuracy ratio, an essential performance metric in classification tasks, is the ratio of components that are correctly classified (TP or TN) to the total number of components that are either TP, TN, FP, or FN.

$$Accuracy = TP + TN /TP + FN + TN + FP$$

Table 1: Analysis of Performance metrics for MLP, SLP and Auto encoders

Metrics	MLP	SLP	Autoencoders
Accuracy	99.411	95.953	98.235
F1 score	99.613	96.044	98.850
Precision	99.230	96.590	97.727
Recall	99.411	95.505	98.235

	precision	recall	f1-score	support
0	1.00	0.98	0.99	41
1	0.99	1.00	1.00	129
accuracy			0.99	170
macro avg	1.00	0.99	0.99	170
weighted avg	0.99	0.99	0.99	170

Figure 5.Performance Metrics for Multilayer

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Perceptron

	precision	recall	f1-score	support
-1.0	0.00	0.00	0.00	0
0.0	1.00	1.00	1.00	42
1.0	1.00	0.95	0.98	131
2.0	0.00	0.00	0.00	0
7.0	0.00	0.00	0.00	0
accuracy			0.97	173
macro avg	0.40	0.39	0.40	173
weighted avg	1.00	0.97	0.98	173

Figure 6.Performance Metrics for Single layer Perceptron

	precision	recall	f1-score	support
0	1.00	0.93	0.96	41
1	0.98	1.00	0.99	129
accuracy			0.98	170
macro avg	0.99	0.96	0.98	170
weighted avg	0.98	0.98	0.98	170

Figure 7.Performance Metrics for Autoencoders

Accuracy Comparison
The highest accuracy is obtained by MLP as it has True Positive (TP) of 1.0, True Negative (TN) of 0.975, False Positive (FP) of 0.024 and False Negative (FN) of 0.0 . The SLP has TN of 0.976, TP of 0.96, FP of 0.023 and FN of 0.3 while autoencoders has TN, TP, FN, FP of 0.92, 1.0, 0.07, 0.0 of values respectively shown in Figure 8.
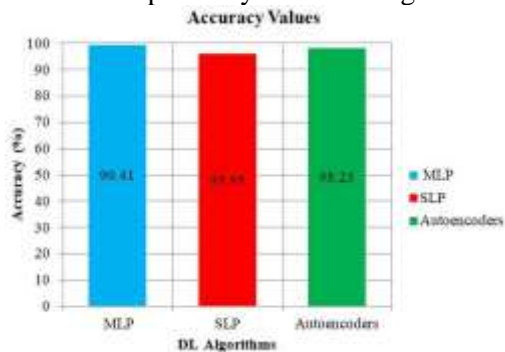

Figure 8. Accuracy comparison between MLP, SLP and autoencoders
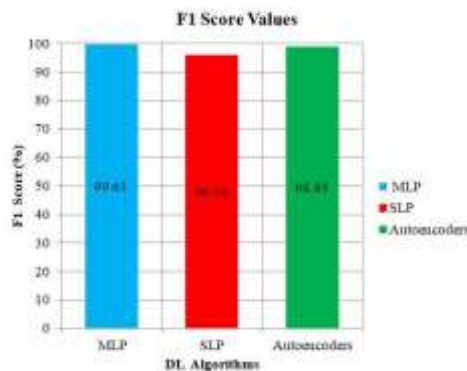
F1 Score Comparison

Figure 9 .F1 score comparison between MLP, SLP and autoencoders

The highest f1 score is obtained by MLP as it has Precision of 99.23 and Recall of 99.41 . While SLP has a Precision of 99.15 and Recall of 96.53 and autoencoders has Precision and Recall of 97.27 and 98.23 values respectively shown in Figure 9.
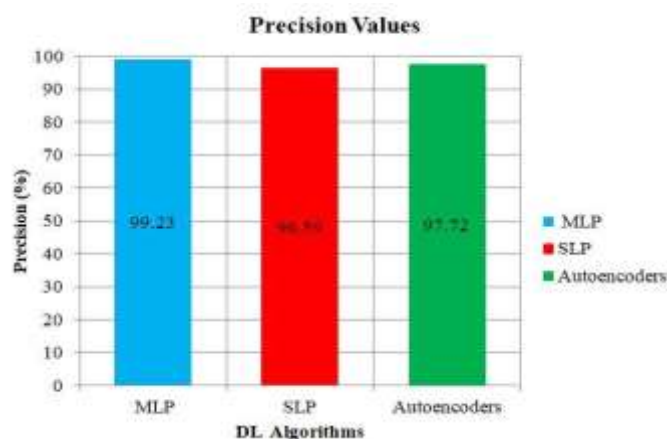

Figure 10 Precision comparison between MLP, SLP and autoencoders

The highest precision is obtained by MLP as it has True Positive (TP) of 1.0 and False Positive of 0.024 . The SLP has a TP of 0.96 and FP of 0.023 while autoencoders has TP and FP of 1.0 and 0.07 values respectively shown in Figure 10.
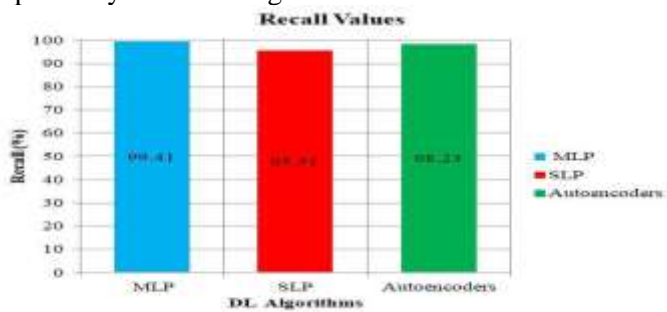

Figure 11. Recall comparison between MLP, SLP and autoencoders

The highest precision is obtained by MLP as it has

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True Positive (TP) of 1.0 and False Negative of 0.0 . The SLP has a TP of 0.96 and FN of 0.03 while autoencoders has TP and FP of 1.0 and 0.0 values respectively shown in Figure 11.

Confusion matrix: The confusion matrix is a tool used to assess the effectiveness of a classification model. Its purpose is to evaluate the model's ability to correctly identify true positives, true negatives, false positives, and false negatives. By comparing the predicted and actual values of a dataset, the matrix provides insight into how accurate the model's predictions are. The data gathered from a confusion matrix can be utilized to calculate different performance metrics, including precision, recall, F1 score, and accuracy, to assess the model's overall performance as shown in Figure 12.
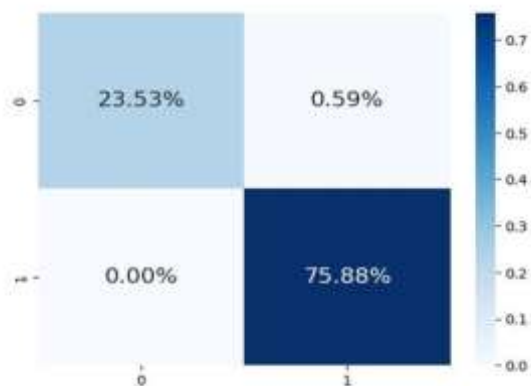

Figure 12 Confusion matrix for Multilayer Perceptron

This provides a visual representation of the performance of a Multilayer Perceptron model through normalizing the values in the confusion matrix by dividing each element by the total number of samples in the matrix, which is obtained by summing all the elements. This normalization allows for a better visualization of the relative proportions of correctly and incorrectly classified samples are shown in Figure 13.
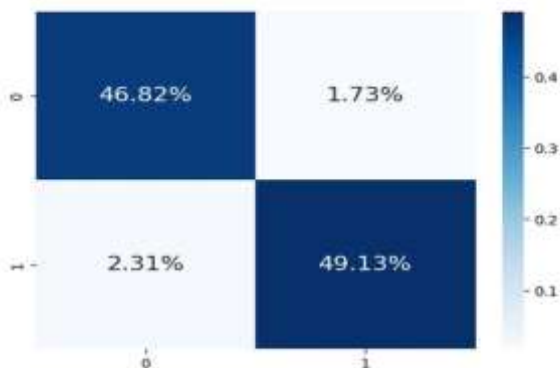

Figure 13 Confusion matrix for Singlelayer

Perceptron

This provides a visual representation of the performance of a Single layer Perceptron model through normalizing the values in the confusion matrix by dividing each element by the total number of samples in the matrix, which is obtained by summing all the elements. This normalization allows for a better visualization of the relative proportions of correctly and incorrectly classified samples.

This provides a visual representation of the performance of a Autoencoders model through normalizing the values in the confusion matrix by dividing each element by the total number of samples in the matrix, which is obtained by summing all the elements. This normalization allows for a better visualization of the relative proportions of correctly and incorrectly classified samples are shown in Figure 14.
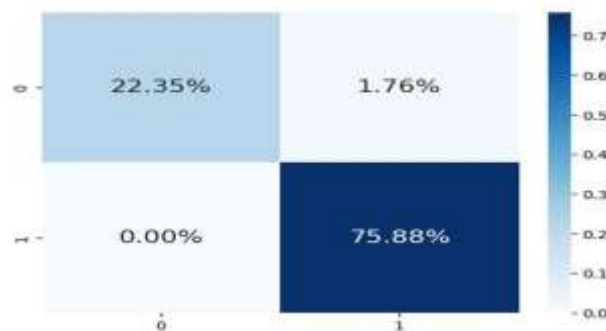

Figure 14 Confusion matrix for Auto encoders

5. Conclusion & Future Work

The proposed research article presents a substantial innovation in the domain of the early diagnosis of liver failure through the deployment of deep learning algorithms. By using the Single Layer Perceptron, Multi-Layer Perceptron and auto encoders' algorithms and training them over a comprehensive dataset of liver images, a new approach has been effectively developed for timely and precise detection of the dysfunction of liver. The results of the proposed study reveal the effectiveness of the algorithms in retrieving the complicated features and patterns out of the medical images thus permitting the early detection of liver failure. The presented work will serve as a catalyst for the forthcoming examinations, encouraging the incorporation of deep learning techniques into routine clinical works and eventually leading to improved forecast and administration of liver failure patients. Further research and clinical trials

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are warranted to evaluate the effectiveness of this approach in real-world scenarios and validate its practical applicability.

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Conflict of Interest
The authors have no conflicts of interest to declare that are relevant to the content of this article.