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| RESEARCH ARTICLE

Detection of Nonalcoholic Fatty Liver Disease Using Deep Learning Algorithms

Sakib Rokoni[1] ✉ Sihab Sarar Chistee[2], Protik Kanu[3], Urmi Ghosh[4], Ashik Ahamed Raian[5] and Labib Rokoni[6]
[16]*Department of Computer Science and Engineering BRAC University, Dhaka, Bangladesh*
[245]*Department of Computer Science and Engineering Daffodil International University, Birulia, Savar, Dhaka, Bangladesh*
[3]*Department of Computer Science and Engineering United International University, Dhaka, Bangladesh*
Corresponding Author: Sakib Rokoni, **E-mail**: sakib.rokoni@g.bracu.ac.bd

| ABSTRACT
Some occasional drinkers develop Nonalcoholic Fatty Liver Disease (NAFLD). Hepatocytes are the key indication of NAFLD. Western nations are seeing rising non-alcoholic fatty liver disease (NAFLD). About 25% of Americans have this chronic liver condition. Recent research estimates that 33.66 percent of Bangladeshi adults have fatty liver disease, affecting over 45 million people. This illness is a major cause of liver-related deaths. Thus, minimizing fatty liver disease risk is crucial. Failure to diagnose fatty liver early may cause serious medical consequences. This study examines fatty liver signs and disorders to help diagnose diabetes early. This study shows the association between fatty liver symptoms and illness to help diagnose early. Deep learning categorization methods are widely utilized to build patient risk prediction models. In this study, "used" was utilized. This article uses numerous deep learning approaches to predict fatty liver disease. Convolutional, Long Short-Team Memory, Recurrent, and Multilayer perception neural network designs were mentioned. This study calculates AUC, shows correlation matrices, and visualizes features, and the optimum method. Deep learning achieved 71% accuracy in a highly categorized environment.

| KEYWORDS

Liver disease, deep learning, detection, classifier

| ARTICLE INFORMATION

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1. Introduction
A complicated and innate medical issue is liver disease. The intricate interaction of several factors affects the development of various disorders. The framework takes into account a number of traits, including genetic predispositions, racial and ethnic origin, sexual orientation, and the effects of environmental factors. People frequently mistakenly believe that having a fatty liver is the only cause of heartburn or other gastrointestinal problems. However, it is important to recognize that this claim lacks proof and empirical backing. When used with alcohol, there is a chance that some medications might cause hepatic steatosis. It should be mentioned that viral illnesses, including hepatitis B and C, have the potential to affect the liver, leading to the accumulation of additional fat within this anatomical structure. Several variables, such as elevated blood sugar levels, cholesterol levels, and obesity, have an impact on the syndrome. Common names for the aforementioned ailment include nonalcoholic fatty liver disease. In conclusion, this condition is referred to medically as non-alcoholic fatty liver disease (NAFLD).

Currently, the prevalence of fatty liver disease is estimated to impact around 20% of the global population. The worry about fatty liver stems from its potential associations with lung cancer, liver failure, and the necessity of undergoing a kidney transplant. Excessive accumulation of fat in the liver can lead to persistent tissue inflammation, potentially exacerbating real damage. Fatty liver disease is characterized by three primary causes, namely, obesity, diabetes mellitus, and hypercholesterolemia. Fatty liver disease, a rather infrequent condition, was observed in pediatric patients. The accumulation of adipose tissue within hepatic cells leads to cellular enlargement or the initiation of an inflammatory response. The condition is often known as non-alcoholic steatohepatitis (NASH). There may be delayed liver damage throughout the nasal phases when tissues are enlarged, the scar forms and we call it scarring.

The prevailing consensus among clinical investigations suggests that the prevalence of the primary etiologies of liver disease ranges from 25% to 45%. The existence of hepatitis steatosis can be indicated by substantial evidence, including many factors that contribute to the formation of fat, such as high alcohol intake, prolonged use of steatogenic drugs, and monogenic hereditary abnormalities. Patients with non-alcoholic fatty liver disease (NAFLD) are at risk of developing cirrhosis and liver failure due to the activation of an inflammatory environment caused by NAFLD. This inflammatory milieu worsens hepatic damage and contributes to a portion of the mortality associated with NAFLD. Non-alcoholic fatty liver disease (NAFLD) has gradually evolved over a period of time. The presence of steatosis, lobular inflammation, and liver ballooning are the most cost-effective histological criteria for diagnosing non-alcoholic steatohepatitis (NASH). This is nonalcoholic fatty liver disease. Fatty liver disorders may affect a considerable number in this group. Those with high blood pressure, obesity, hyperlipidemia, and diabetes are included.

There are no symptoms present when the illness first manifests. However, about 10-15% of patients have been reported to have a tightness or weight in the upper right region of their stomach. The existence of the aforementioned illness may be the cause of this phenomenon. There are no other symptoms that have been noticed alongside these symptoms, which often appear later in the course of the disease. Effective therapy depends on early sickness discovery. Currently, physical examinations like ultrasonography may be used in the diagnosis process for fatty liver. The use of a pelvic ultrasound method, with a focus on prioritizing the examination of the kidneys, can also be used to detect the existence of a highly adipose liver. A biopsy process may be used to confirm the existence and determine the severity of a medical disease. An unhealthy liver is one that has a fat content of more than 5%. Despite the widespread acceptance of liver biopsy as the only reliable way to determine the severity of non-alcoholic steatohepatitis (NASH) and non-alcoholic fatty liver disease (NAFLD), it is still often used. Moreover, using pictures as illustrations the computation of these findings involves a substantial time commitment and a high level of difficulty.

Evidence from recent research indicates the positive effects of coffee drinking on patients with liver disease. The risk of liver damage and liver cancer in those with fatty liver disease may be reduced by drinking two to three cups of coffee daily. Avoiding grains including wheat, rice, potatoes, and maize is recommended for those with fatty liver disease. Furthermore, it is recommended that patients increase their intake of vegetables and salads while reducing their consumption of fatty meats. The migration of neutrophils towards liver tissues in response to hepatocyte injury is a phenomenon that has been seen, however, the precise mechanism behind this process remains to be fully elucidated.

Finally, daisies are classified as fibrosis due to the fact that chronic hepatitis C can induce the development of fibrotic tissue in the stellate cells of the liver. In the advanced phases of steatohepatitis, individuals may have minimal or nonspecific symptoms, such as fatigue or melancholy. The fibrosis process perpetuates the structural integrity of the organ, while those with cirrhosis are classified as economically disadvantaged.

Pain in the right upper quadrant of the abdomen, jaundice, and ascites may manifest following significant liver injury, characterized by the buildup of fluid in the peritoneal cavity. The study employed the following criteria. Determining whether an individual is afflicted with liver disease is of paramount importance. The body exhibits several symptoms, such as weakness, weariness, abrupt weight loss, nausea, vomiting, and skin yellowing, which are indicative of jaundice. The phenomenon of visual fuzziness refers to a subjective experience in which one's visual perception lacks clarity or sharpness. The primary objective of this inquiry is to examine the Liver's prognosis, with the aim of enabling individuals to respond effectively in order to control the condition within its early stages. This is conducted with the purpose of determining the many symptoms and their correlation to the underlying cause of the liver.

Finally, the outcomes of this investigation will enable us to select the most effective deep learning classifier for liver prediction.

Our objective is to prevent the formation of fat in the liver. In order to reduce the extent of hepatic fibrosis associated with non-alcoholic fatty liver disease. Lastly, it prevents the occurrence of liver failure and cancer.

2. Literature Review

The research done by Okanoue et al [2021] a liver condition using deep learning methods. Deep learning techniques, such as the participants engaged in a thorough investigation of the development of an exceptional and notable study known as Non-Alcoholic Steatohepatitis (NASH). The research effort made use of the latest artificial intelligence (AI) and neural network (NN) technologies to identify the presence of non-alcoholic steatohepatitis (NASH) and non-alcoholic fatty liver disease (NAFLD). The non-alcoholic steatohepatitis (NASH) spectrum expands inside the curve created by the value and receiver operator.

Identifying Non-Alcoholic Steatohepatitis (NASH) from Non-alcoholic Fatty Liver Disease (NAFLD): Training or validity is not relevant to the current study. We can see that different percentages are being compared to one another in the data above. These include 9.7% against 79.7%, 99.8%, against 99.8%, 99.7% against 99.7%, 99.8% against 99.7%, 99.7% against 99.7% against 99.8% against 0.999. The success rates of 90.5% compared to 99.5%, 84.3% compared to 93.3%, 98.2% compared to 98.0%, 98.6% compared to 73.7%, and 0.960% compared to 0.950% show the capacity to distinguish between the nasal areas. The user's text isn't specific enough for a scholarly revision. Please elaborate, even after splitting the output data into two separate portions, the findings were astounding and showed no uncertainty. Constantinescu [Constantinescu et al 2021] categorizes cases of fatty liver, the researchers used a variety of Convolutional neural network (CNN) designs. Images of illness can be graphically portrayed by using medical markers and pixels. Their models were trained and evaluated using a total of 629 data points. Both general stagnation and hepatic stagnation are depicted in these paintings. The method of studying deeply and extensively to gain information and insight. The algorithms suggested for identifying stasis and classifying images of the liver into normal and fatty liver show a notable level of effectiveness. The test results show a performance level that is no more than 90%. To determine the possible users of these algorithms in a healthcare setting, more research is necessary. With test accuracy of 93.23%, sensitivity of 89.9%, accuracy of 96.6%, and receiver operating characteristic (ROC) area under the curve (AUC) values of 0.93 for each receiver, the recommended models, which make use of the Inception V3 architecture, perform well. A test accuracy of 90.77%, as well as a sensitivity and accuracy of 7.9%, were obtained utilizing other suggested models that used VGG-1. Additionally, these models generated an accuracy of 92.85% and an area under the curve (AUC) for the receiver operating characteristic (ROC) of 0.91. Convolutional neural networks (CNNs), comprehensive understanding, hepatic steatosis, and non-alcoholic fatty liver disease (NAFLD) were used as terminology. Hectors et al. [2021] have demonstrated good diagnostic skills in staging liver fibrosis using fully automated deep learning models that showed

Diagnostic performance comparable to magnetic resonance elastography (MRE). For F1-4, the deep learning (DL) area under the receiver operating characteristic curve (AUC) values were 0.99, 0.70, and 0.77 for the training, validation, and test sets, respectively.

The AUC values for F2-4 were respectively 0.92, 0.71, and 0.91. The AUC values for F3-4 were also 0.91, 0.78, and 0.90, respectively. Finally, for F4, the corresponding AUC values were 0.98, 0.83, and 0.85. Phan et al. [2020] Viral hepatitis's fundamental goal is inherent in its underlying etiology. These illnesses may display specific symptoms in the latter stages, although there may or may not be a causal relationship between them. People who were Taiwanese citizens carried out research between the years 2002 and 2010.

According to the Annual Percent Change (AAPC), the aforementioned proportion is changed by 5.8%, with a 95% confidence range (CI) ranging from 4.2% to 7.4%. Youth, defined as those between the ages of 16 and 30, had a negative trend, with an average annual percent change (AAPC) of 5.6. The 95 percent confidence interval for this result ranges from 8.1 to 2.9. According to its analysis of deep learning (DL) models, the Convolutional Neural Network (CNN) model had the greatest prediction accuracy of 0.980 in predicting liver cancer. For this study, the AUC (area under the receiver operating characteristic curve) value is 0.886. For the goal optimization, CNN uses an algorithm that has a noteworthy accuracy rate of 95%,98% accuracy rate is achieved. Pati et. al. [2021] and others (2015) based on the results of their investigation, have shown that cirrhosis is more common in men than in women, with alcoholic liver disease being its main cause. In 50% of the patients, there was a high frequency of H. pylori infection and early presentation 57.4% of those with cirrhosis had Helicobacter pylori infection, according to the study. The proportion is 70%,96% of patients with alcoholic liver disease (ALD) and 50% of those with cryptogenic cirrhosis had H. pylori infection. However, RUT was not present in any of the chronic cirrhosis cases brought on by the hepatitis B virus (HBV). The investigation done by Han et al. [2020] The application of deep learning algorithms with radiofrequency ultrasonography data showed a good degree of accuracy in the detection of nonalcoholic fatty liver disease and the estimation of hepatic fat percentage after ruling out other causes of steatosis. Non-alcoholic fatty liver disease categorization scores were produced using the binary classifier. Square brackets indicate confidence intervals with a 95% level of confidence, while percentages inside brackets stand in for fractions.

Time gain compensation (TGC) is a method for adjusting the amplification of received signals depending on the time of flight that is employed in a variety of industries, including Ultrasonography and medical imaging. The negative predictive value is referred to by the abbreviation NPV. The abbreviation PPV stands for positive predictive value. The user has given a numerical value of 97. The term "sensitivity" refers to an organism's or system's capacity to recognize and react to the calculated degree of granularity is 94%, with a 97% positive predictive value (PPV). 96% of predictions are correct. Arjmand et. al. [2019] A deep learning approach's primary goal is to identify the presence of biopsy probes in various species. The spectrum of clinical symptoms associated with non-alcoholic fatty liver disease (NAFLD) includes cirrhosis, steatohepatitis, and hepatocellular encephalitis. In their investigation, the researchers used a total of five machine learning models, including CNN (reaching an accuracy rate of 93.3%), SGDM, backpropagation methods, and other optimization approaches. The 95% accuracy rate. The people involved in the RF echo data analysis and interpretation. In 2018, Dandan et. al. [2019] Utilized deep learning techniques to make predictions about conditions affecting the liver. The researchers' work serves as an example of how data mining and statistical techniques may be used to create prediction models that use patient specific data to anticipate the course of sickness in clinical settings. The researchers used a Convolutional Neural Network (CNN) as well as two other techniques to extract texture information from images: Wavelet Multi-sub-bands Cooccurrence Matrix (WMCM) and Multi-scale Gray-level Cooccurrence Matrix (MGLCM). The data is collected using a light gradient boosting machine (GBM) classifier. Hepatic fibrosis and fatty liver disease occur at relative rates of 82.1%, 85.0%, and 80.9%, respectively 85.4% of the data is accurate. The utilization of the envelope signal and grayscale values played a crucial part in the diagnosis of non-alcoholic fatty liver disease (NAFLD). An area under the receiver operating characteristic curve (AUC) of greater than 0.7 indicated that the three methods were particularly sensitive in detecting non-alcoholic fatty liver disease (NAFLD). However, as indicated by its value of o.958, the region under the curve of receiver operating characteristic (AUC) of the deep-learning index demonstrated a superior capacity to differentiate between moderate and severe nonalcoholic fatty liver disease (NAFLD).

Convolutional neural networks (CNN), the VGG16 model with Transfer Learning, and the VGG16 model with Transfer Learning and Fine Kernal were used in the study by Reddy et al. [2018] to analyze liver disease. Convolutional neural network (CNN) attained an accuracy of 89% sensitivity of 85%, and a specificity of 84.3% in this particular case 95%, 85%, and 90.6%, respectively, are the corresponding accuracy values for VGG16 with Transfer Learning and VGG16 with Transfer Learning followed by Fine Tuning. The proposed approach produced a receiver operating characteristic (ROC) of 0.96. Yao [2020] and associates (2012) the authors of this deep learning study presented DenseDNN, an architecture of a neural network created especially for the identification of liver disorders. Model Comparisons of Different Features The text “LR” has been supplied by the user. The given sequence of integers, 0.3412, 0.4794, 0.5690, 0.6416, 0.7003, 0.7986, 0.8353, and 0.8790, and lastly 0.5643, 0.6884, and 0.7604. Accuracy ratings for the DenseDNN model were 0.5840, 0.7068, 0.7737, 0.8204, 0.8565, and 0.8919.

3. Algorithm Description

Here is a list of the algorithms that were used in this study. Descriptions are talked about four different methods used to measure success in this study.

3.1 Convolutional Neural Networks:

Convolutional Neural Networks, also referred to as Deep Learning systems may take an input image, apply the appropriate weights and biases to different traits and features in the pictures, and then categorize the image as needed. CNN is a common technique in the domains of pattern detection and processing of images. Only a few of its numerous benefits include simplicity, a small number of training parameters, and adaptability. The feature map layer, the second, contains feature maps particular to each compute layer in the network [CNN 2023].

3.2 Recurrent Neural Networks:

Recurrent neural networks utilize the process of changing parameters, remembering previous outputs, and converting independent activations into dependent activations is made simpler by passing each output into the following hidden layer. RNNs in general and LSTMs in particular have been the most successful in the field of natural language processing, which focuses on word and paragraph sequences. They are also employed as generative models for tasks like producing handwriting that require a sequence output, in addition to their use with text [RNN 2018].

3.3 Long Short Term Memory Networks:

The deep learning architecture for LSTM (long short-term memory) (RNN) includes a synthetic recurrent neural network. When categorizing, analyzing, and making predictions using time series data, Long Short-Term Memory (LSTM) networks excel.

This is partly because they can manage circumstances where there are temporal delays between important time-series events that are of undetermined length.

A recurrent neural network’s control flow resembles an LSTM network’s long short-term memory (LSTM) network. While concurrently transferring the information, the system processes data in real time. LSTM cells display a variety of capabilities via unique processes. The Long Short-Term Memory (LSTM) model makes use of certain processes to make it easier to remember or forget information. In tasks involving sequence prediction, the LSTM network, a kind of recurrent neural network, has the capacity to learn about order dependency. This is essential in a number of complex problem fields, including but not restricted to speech recognition and machine translation.

There are several difficulties in mastering the subject of Long Short-Term Memory (LSTM) in deep learning. There is nothing in the user’s content that has to be rewritten [Brownlee 2022].

3.4 Multilayer Perceptions:

A multicolored artificial neural feed-forward network is referred to as a “multicolored (MLP) sensor”. The input, hidden, and output node layers are the minimum number of layers that make up an MLP. Apart from the input of nodes, each node is an anti-linear activation function. The supervised learning method of teaching backpropagation is used by MLP. The MLP differs from a linear perceptual by employing nonlinear activation and having multiple layers. There is information that is unable to be divided in a linear fashion [Brownlee et al 2018] [Emon et al 2020] [Islam et al 2020].

3.5 Proposed Model

Figures and Table 1 are commonly used in academic research to provide data and information in a visual format. These visual aids are effective in conveying complex information in a concise and organized Figure 1 provides a concise depiction of each component inside our suggested model.

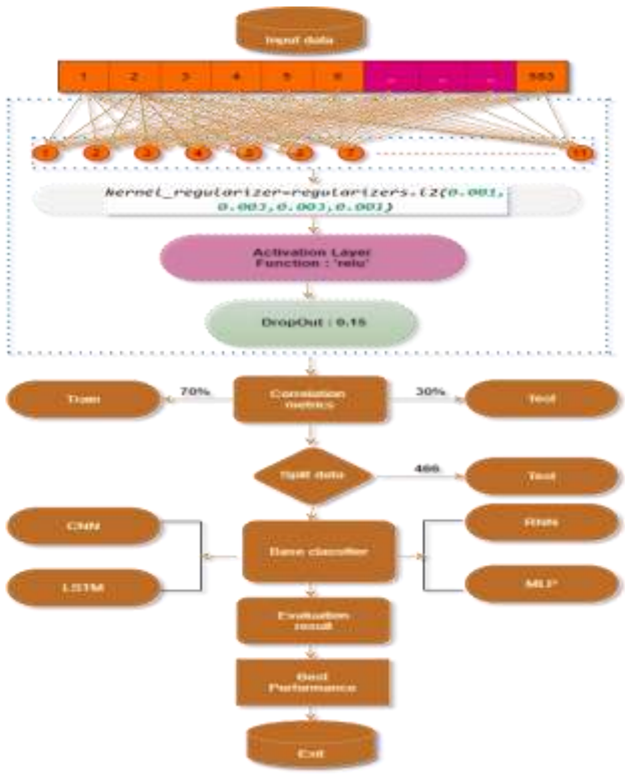

Fig.1.Step-by-step Model Propose Procedure

1) Input Data: A total of 583 data points were utilized in the present investigation. There is a total of 11 qualities in the dataset, all of which are represented as floating-point data. Additionally, it is worth noting that 11 of these properties are observable. The data utilized in this investigation was sourced from the UCI Machine Learning Repository.

2) Measures for Correlation: Figure 2 displays correlation measurements.

3) Divide Data: In the current research, the model was trained using 70% of the data and then tested using the remaining 30%.

4) Basic Classifier: The fundamental classifier uses Long Short Term Memory Networks and Convolutional Neural Networks.

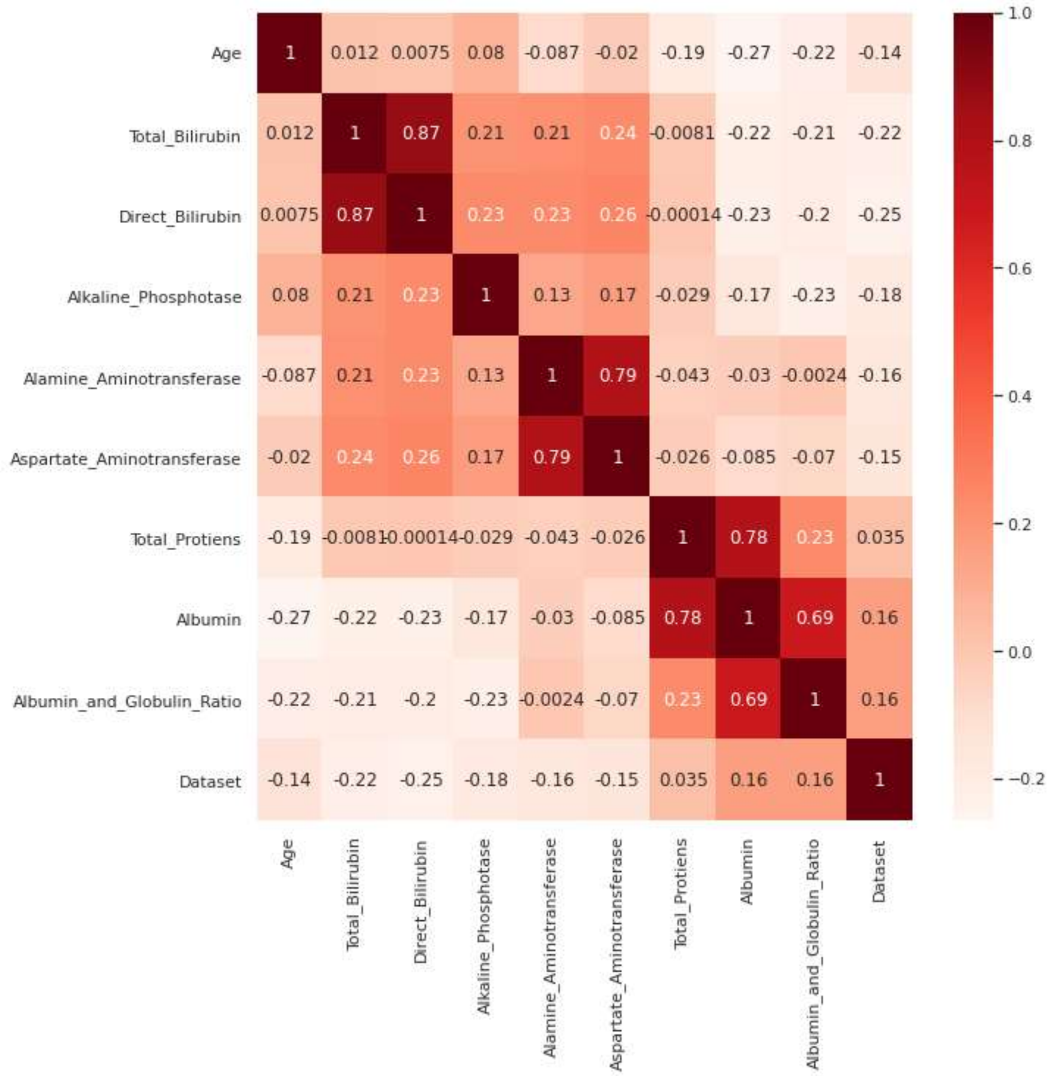

Figure 2. Correlation metrics

5) Result: The classification report shows all algorithms' confusion matrix, precision, recall, and other findings.

6) Best Algorithm: The results of this study are contingent upon certain aspects of the research conducted. Nevertheless, the most optimal algorithms in our research are those that yield the highest accuracy in terms of true positive, false positive, true negative, and false negative outcomes.

4. Results Discussion and Analysis

The confusion matrix of the classifier application is depicted in Table 1 of this research. The LSTM and CNN models are considered to yield the most favorable outcome for sequence classification in the ILPD dataset. Long Short Term Memory Networks (LSTMs) and Convolutional Neural Networks (CNNs) are two distinct types of neural networks.

In Table 2, classification outcomes are displayed.

Here, we analyze precision, recall, f-measure, and AUC (area under the curve).

Precision: People who work in information recovery count on getting accurate records [18]. For example, the number that comes up when you do a text search on a bunch of papers is correct.

Recall: A small proportion of the relevant records effectively garnered during information gathering are retrievable. For instance, when conducting a text search on a collection of documents, the ratio of accurate results to total results to be retrieved is remembered.

F-measure: The F-measure, often known as the F-score, is a measurement of a test's accuracy used in the statistical evaluation of binary categorization.

AUC: The AUC gives a full picture of how well a model meets all reasonable classification standards. AUC can mean a lot of different things, and one of them is that the model works better than a random negative random positive.

TABLE 2, shows the accuracy, f-1 score, precision, area under curve (AUC), and memory value of the models for the testing dataset Long Short Term Memory Networks (LSTM) have the best accuracy. A score of 85% means it is correct.

Table 1
The results of classification confusion measures.

Model	Accuracy(%)	Label	Prediction Negative	Prediction Positive
LSTM	87	Actual Negative Actual Positive	19	6
Adam	74	Actual Negative Actual Positive	0 1	12 0
Adamax	75	Actual Negative Actual Positive	0 33	33 0
CNN	78	Actual Negative Actual Positive		
MLP	50	Actual Negative Actual Positive	12 10	89 12

Table 2
Implementing classifier results

Model Name	Class	Precision (%)	Recall (%)	F1-score avg (%)	Accuracy(%)
LSTM	0 1	89 87	87 90	88 89	88
Adam	0 1				74
Dense	0 1	36 53	50 78	42 61	78
CNN	0 1				79
MLP	0 1	89 87	87 90	88 89	50

5. Conclusion

The results of this study suggest that deep learning models are well suited for meaningful prediction of NAFLD. The LSTM and CNN models are considered to yield the most favorable outcome for sequence classification in the ILPD dataset. In recent years, traditional diagnostic and treatment plans have been contributing to an improved understanding of NAFLD. But it sometimes has adverse effects and wastes resources. However, Deep learning models always provide a significant insight compared with traditional statistical models. We, therefore, developed and evaluated a deep learning method to predict NAFLD.

This study calculates AUC, shows correlation matrices, and visualizes features, and the optimum method. To our knowledge, this is the first study that attempted to predict NAFLD using various deep learning models. Hence, the performances of different models are the most important consideration, along with the ease of use and the interpretation of the models. Our finding suggests that the Long Short-Term Memory Networks (LSTMs) outperform all other methods with an accuracy of 88% which would be the best option to implement a system for predicting fatty liver disease patients appropriately and effectively. This method may be more insightful in real-world clinical practice. Deep learning models would assist in effectively identifying NAFLD for preventive and therapeutic purposes.

This present study has some limitations that need to be addressed. First, we only collected data from one medical center. However, multicenter datasets and external validation could have better performance and be more reliable. The dataset comprises 584 patient pieces of information that were considered as sample size although most of the variables were statistically significant. In the future, we need more data for better results.

In the future this research will integrate machine learning and AI techniques hold great promise for advancing the analysis and forecasting of liver illness. By leveraging these technologies, we can delve into extensive datasets, encompassing patient medical records, genetic information, and lifestyle data, to unveil intricate patterns and correlations associated with liver diseases. AI models, adept at analyzing medical imaging data, can offer diagnostic support by identifying subtle signs of liver damage. Furthermore, we can optimize treatment plans by considering patient responses to different medications, ensuring efficacy and minimizing adverse effects. Real-time monitoring systems powered by AI can provide continuous assessment of liver health, benefiting individuals with chronic conditions. Genomic analysis using machine learning can uncover genetic markers influencing susceptibility to liver diseases, contributing to targeted therapeutic approaches.

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ORCID iD:
[1] https://orcid.org/0000-0002-0160-4354
[2] https://orcid.org/0009-0003-1396-4837
[3] https://orcid.org/0009-0003-8645-2541
[4] https://orcid.org/0009-0001-7313-6190
[5] https://orcid.org/0009-0002-1402-6263
[6] https://orcid.org/0009-0009-8127-1585

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Author's Biography

Sakib Rokoni, Department of Computer Science and Engineering BRAC University,
66 Mohakhali, Dhaka, Bangladesh.

Sakib Rokoni was born in Sirajganj, Rajshahi, Bangladesh. He received his Bachelor's degree in Computer Science and Engineering from Daffodil International University, Bangladesh, in 2023. He was hired by a renowned IT company named Intelsense AI Limited as a Software Engineer. He has been working with the company from 01 September 2022 to 31 April 2023. Recently he has been pursuing a Master's degree in Computer Science and Engineering from BRAC University, Dhaka, Bangladesh. His current research interests include Machine learning, Deep Learning, Artificial intelligence, NLP, Computer Vision, and FSO Networking. He can be reached at email; sakib.rokoni@g.bracu.ac.bd

Sihab Sarar Chistee, Department of Computer Science and Engineering Daffodil International University, Dhaka, Bangladesh.

Sihab Sarar Chistee is Solution-oriented and problem solver with building and maintaining software and software architecture. He is fascinated by computers and their capabilities. This fascination led me to delve into the world of coding and software development at a young age, experimenting with simple programs and games. My passion for technology only grew stronger as they progressed through my academic journey. Excelling in mathematics and science throughout school, I recognized that my interest lay in exploring the intricacies of computing. This realization prompted me to pursue a degree in Computer Science at Daffodil International University. During their undergraduate years, I actively participated in various coding competitions, hackathons, and tech-related clubs. My commitment and dedication not only earned them accolades but also provided me with invaluable practical experience. I developed a keen understanding of programming languages such as Python, Java, C++, and more, and honed my skills in software development, algorithms, and data structures. I am also a budding computer science enthusiast passionate about exploring the dynamic world of research. Today, I stand as a testament to the potential of combining passion with dedication in the field of Computer Science. With a trailblazing spirit and an unwavering commitment to innovation, I continue to push the boundaries of technology, striving to make the world a better, more connected place through their contributions to the ever-evolving landscape of computing. He can be reached at email; sihab15-12389@diu.edu.bd

Protik Kanu Department Of Computer Science and Engineering,
United International University, Dhaka, Bangladesh.

Protik Kanu has completed his BSc in Computer Science and Engineering from United International University, Bangladesh. He is currently working as an Information technology business analyst in MetLife Bangladesh. He is passionate about research and analytical activities. His areas of interest in research are cloud computing, Machine Learning, and informatics. He can be reached at email; protikkanu111@gmail.com

Urmi Ghosh, Department of Computer Science and Engineering,
Daffodil International University, Dhaka, Bangladesh.
Urmi Ghosh is an undergraduate with a BSc in Computer Science and Engineering from Daffodil International University. She is currently working as a Web Developer Intern. She is passionate about research and analytical activities. Her areas of interest in Machine Learning and Deep Learning. She can be reached at email; urmi15-13225@diu.edu.bd

Ashik Ahamed Raian Department of Computer Science and Engineering,
Daffodil International University, Dhaka, Bangladesh.
Ashik Ahamed Raian is a highly accomplished and passionate researcher from Bangladesh. He has consistently demonstrated his commitment to academic excellence and innovation throughout his career. A proud alumnus of Daffodil International University, Bangladesh, he graduated with a Bachelor of Science in Computer Science and Engineering. He is dedicated to refining existing deep learning models, enhancing their applicability to a wide array of real-world scenarios while simultaneously reducing their complexity and bolstering interpretability. He can be reached at email; ashik15-12193@diu.edu.bd

Labib Rokoni, Department Of Electrical and Electronic Engineering, BRAC University,
66 Mohakhali, Dhaka, Bangladesh.
Labib Rokoni was born in Sirajganj, Rajshahi, Bangladesh. He is currently pursuing a Bachelor's degree in Electrical and Electronic Engineering at BRAC University, Bangladesh. His current research interests include Power Systems and Control Theory, Condition monitoring of electrical equipment, VLSI, Electronic System Design, Signal Processing, and Machine Learning. He can be reached at email; labib.rokoni@g.bracu.ac.bd