

AI-Powered Healthcare Diagnostics: Innovations in Personalized Medicine

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Abstract: Advances in AI are transforming healthcare diagnostics, enabling early detection and personalized treatment plans. This paper explores AI-powered solutions for healthcare applications, focusing on the integration of machine learning models into diagnostic workflows. Fatty liver disease is widely spread in the current era as it occurs based on the population factor as it gets increasing drastically. This disease spreads vastly and it results in sickness and death. It needs some early identification and diagnosis so that the patients can able to take some necessary measures to go through some earlier treatment, diagnosis, etc. So, here improper data analysis and diagnosis leads to some critical problem is considered. Here, a novel ML-based Random Forest approach is proposed in order to predict fatty liver disease as it classifies the risk factor of the individual patient to perform prevention of disease, early diagnosis, etc. The framework combines predictive analytics, image-based diagnostics, and patient-specific data to improve accuracy and efficiency. Case studies on fatty liver is identified based on the images of ultrasound and it helps to identify the disease and prediction uses certain variable of this disease to perform effective identification, decision making, etc. through this learning model. Demonstrate enhanced diagnostic capabilities and improved patient outcomes. The research highlights the potential for AI to revolutionize healthcare, particularly in personalized medicine. The effectiveness of this approach is analysed based on prediction accuracy, data specificity, data sensitivity with positive and negative value. The proposed model is compared with some existing models such as, e logistic regression (LR), Random Forest (RF), artificial neural networks (ANNs) and k-nearest neighbors (KNNs).

Keywords: AI in Healthcare, Personalized Medicine, Healthcare Diagnostics, Predictive Analytics, Machine Learning, machine learning, ultrasound, learning, data analysis, prediction.

1. Introduction

In recent days, Fatty Liver Disease (FLD) plays a significant role in the field of medical-based healthcare as it integrates with high illness and humanity. This FLD results in noncholestatic cirrhosis and hepatocellular carcinoma [1]. With respect to FLD, there are certain parallel things and disease happen such as, obesity, diabetes and metabolic syndrome. Based on Fatty Liver Disease (FLD), economic gets downgraded in some scenario. Therefore, accurate identification of those who are at risk and early detection of FLD may be extremely helpful for diagnosis, prevention, or even effective therapy. Over the past ten years, the biopsy has been employed to classify patients and is regarded as a diagnostic gold standard for evaluating liver fatty infiltrate [2]. The adoption of this procedure could result in adverse consequences and sample errors, and it is also very intrusive and expensive. Although ultrasonography is a useful

technique for diagnosing FLD with more precision, the accuracy of identification is significantly operator dependent [3].

Machine learning (ML) is a branch of computer science that use algorithms to find patterns in massive amounts of data and help anticipate different outcomes [4]. Multiple disciplines now have the option of using ML approaches as a tool for prediction and decision-making. Due of the accessibility of clinical data, ML has proven essential in guiding medical judgments as well. Making a real-time, effective healthcare choice would be made easier with the help of a machine learning model, which would be developed. By recognising the appropriate patients with significant multiple risk factors earlier, it would also allow for the optimization of hospital resources [5].

Medical imaging methods like ultrasound (US), computed tomography (CT), and magnetic resonance imaging (MRI) have been the subject of numerous studies in the present day that have looked at them for the classification of fatty liver disease. It is noninvasive, inexpensive, simple to use, and portable to use ultrasound imaging. With the aid of many retrieved features from ultrasound images, Andrade et al. [6] assessed the effectiveness of three classifiers for the diagnosis of hepatic steatosis. Additionally, Li et al. [7] employed support vector machine (SVM) as the classification technique to assess B-mode ultrasonic pictures textural features of fatty liver, construct near-field light-spot density, near-far-field grayscale ratio, grayscale co-occurrence matrix, and neighbourhood gray-tone difference matrix [8].

1.1. Datasets population:

We gathered information from kaggle on fatty liver disease as part of an initiative to safeguard the liver. All patients who had undergone initial fatty liver screening in 2020 were included. If a patient was less than 30 years old, had an incomplete physical examination, or tested positive for fatty liver disease by ultrasonography, they were eliminated from the study. This study, which followed the ethical principles of the Declaration of Helsinki of the international medical association, was examined and approved by the institutional ethics committees board of 605 patients along with certain attributes as mentioned below,

- Gender either male or female
- Patient height and weight
- Body mass index
- Hip Circumference
- Diastolic Blood Pressure
- Diyabetes Mellitus
- Hyper tension and so on.

In this work, the machine learning algorithm helps to perform the identification process and effective treatment process. There are some research gaps identified based on the fatty liver disease datasets, there may be a more significant variation in the data. It leads to the problem of heterogeneity and results in improper diagnosis for the patient. In the prediction process, the

problem of prognosis happens and leads to the frequent happening of disease in the future. As the liver identification process takes a long time and response, it will affect the In-time treatment and lead to high complexity in the treatment process of fatty liver disease.

The proposed framework is not applied to any other liver disease as it needs some modifications. Here are the research limitations of analyzing the complex dataset of ultrasound images as it needs some effectiveness as it requires some fatty liver disease classification process. The limitations of time complexity occurrence are directly proportional to the outcome of the prediction process.

II. Literature Survey

The most serious illness is liver disease, which is also the main cause of death in people. The largest and most important organ in our body is the liver. The exocrine liver gland secretes bile into the gut. According to observations made over the past 20 years, liver disease is one of the top 12 most deadly causes of death and the leading cause of death for adults between the ages of 45 and 54 [9]. An excessive fat buildup in the liver cells is the primary cause of fatty liver disease. Steatosis is the process in which fat is deposited in the liver cells, and it can be brought on by consuming alcohol, pickles, tainted food, etc. as well as by the metabolic syndrome. The primary cause of noncholestatic cirrhosis and hepatocellular liver disease is fatty liver disease [10]. The diagnosis of fatty liver disease has traditionally been made with a biopsy, which is expensive and prone to sample errors (FLD).

Today, ultrasonography aids in the accurate diagnosis of FLD, however operator skill plays a significant role in the accuracy of the diagnosis [11]. A time-aware recommendation system was developed to provide users with movie suggestions using restricted Boltzmann machines, sometimes known as unsupervised neural networks. The identification of skin liver disease and the classification of tweet sentiment into positive and negative using natural language processing are just two examples of how machine learning is crucial in today's world [12]. Machine learning and generative modelling are making significant contributions to a variety of industries, including medicine and recommendation systems. As deep learning is the foundation of machine learning, both of them are playing a key part in every industry, such as COVID19 detection by utilising CNN ranking approach and text recognition [13].

Credit card theft was detected using a variety of machine learning techniques, including Random Forest, Decision trees, etc. In this study, we applied several machine learning methods, such as Gaussian NB, Random Forest, Logistic Regression, KNN, Support Vector Machine, Decision Tree, Gradient Boosting, CatBoost, AdaBoost, LightGBM, and XG Boost, on a subset of the liver dataset's correlation matrix. We then compared all of the results in terms of sensitivity, specificity, precision, Matthews Correlation Coefficient, F1 score, accuracy, confusion matrix.

Machine learning and deep learning disciplines are making significant contributions to the understanding of diseases like liver disease, TB, pneumonia, and other serious illnesses. By evaluating the effectiveness of three distinct classifiers, [14] employed retrieved ultrasound image features to diagnose hepatic steatosis. Classified normal individuals from those who had

fatty liver illnesses such as steatosis, fibrosis, and cirrhosis using an automatic ROI selection and hierarchical technique. A support vector machine to diagnose and examine B-mode ultrasonic pictures of FLD with various textures. When [15] employed the anatomic and echogenic information of ultrasonic images to separate fatty liver ultrasonic images from normal liver ultrasonic images, they used the Bayesian framework to extract features.

[16] classified liver photos from the US liver image collection in 2014 using the SVM classifier, and they reached an accuracy of 84.9%. Signal processing method for classifying fatty liver illnesses based on kurtosis scanning had an accuracy of 81.2% when it was applied to the US liver image dataset. In order to extract characteristics from US liver pictures, Saba et al. used a backpropagation neural network (BPNN). A total of 6 different types of algorithms were used, and BPNN achieved an accuracy of 97.6%.

[17] used the ILPD dataset that was obtained from UCI and implemented the support vector machine and naive bayes classification algorithms using MATLAB. According to the results, SVM performed well and gained higher accuracy than naive bayes, which was 79.66%, but naive bayes required less training time than SVM. In 2014, Dhamodharan et al. The Nave Bayes and F1 tree algorithms for the prediction of liver disorders. The three main liver diseases were categorised as Liver Liver disease, Cirrhosis, and Hepatitis.

Machines play a significant role in the medical industry, helping with tasks like ECG classification, identifying COVID 19 and Pneumonia, detecting Parkinson illness, detecting malaria, and predicting heart disease. Every field has many contributions because machine learning is now the foundation of all the specialised fields. Although the most up-to-date work was generally of high quality, a comprehensive comparison of available algorithms was lacking. There weren't many missing works in the dataset. One of the main causes of mortality in humans is liver disease. Due to the expense of ultrasonic categorization, FLD requires excellent detection accuracy.

[18] proposed Support Vector Machine, Nearfield Light Spot-Density (NFLSD), Near-Far-Field Grayscale Ratio (NFFGR) and its takes the advantages as,

- Proper Diagnosis using nuclear RBF kernel in SVM and Feature extraction technique was good.
- Lacked in metric evaluation part and No comparison with standard machine learning algorithms.

[19] proposed Support Vector Machine, Differential Evolutionary Feature Selection (DEFS) algorithm, Texture Features and its advantages & disadvantages as,

- Usage of advance technique for extraction of features and Proposed CAD system using SVM with accuracy of 84.9 ± 3.2 .
- Accuracy achieved was not high and Dataset used was very small

[20] proposed Back propagation Neural Network Haralick, Basic geometric, Fourier transform, Discrete 15 Cosine Transform, Gupta transform and Gabor transform. The advantages disadvantages are mentioned as below,

- Excellent feature extraction from all six sets of features for online and offline testing Levenberg-Marquardt Back Propagation Network (BPN) classifier as used for classification among normal and abnormal categories and achieves high accuracy.

- Dataset was small

[21] Naïve Bayes, Support Vector and Machine learning approach as it takes certain advantages and disadvantages as listed below,

- Achieved accuracy of 79.66% and Proper evaluation in terms of execution time, accuracy, TP rate, Precision, F measure.
- No comparison with other machine learning algorithms and No preprocessing of dataset.

[17] Naïve Bayes, F1 tree algorithm, WEKA Data Mining tool are proposed as it contains certain advantages and disadvantages as mentioned below,

- Naïve Bayes was best classifier by achieving accuracy of 75.54% and compared both the algorithm in all metrics evaluation
- Lacked in comparison with other studies and Comparison with other ML algorithms were missing.

However, due to the use of various ultrasound machines, the poor quality of the images, and the physical variations of the patients, the diagnosis of fatty liver on ultrasound imaging differs. A prediction model based on readily accessible clinical characteristics, however, would assist doctors in accurately identifying and making a decision regarding prevention, early diagnosis, and focused intervention. The advantages of using classification models with information from the electronic medical record to predict FDL have not yet been thoroughly assessed. Therefore, our goal was to develop a predictive model for fatty liver disease employing cutting-edge machine learning techniques, particularly in the classification method. As far as we are aware, this is the most thorough study that used machine learning models to predict FDL. The research objective is formulated as mentioned below,

- During the process of liver disease detection, treatment and monitoring, data interpretation problems occur due to the larger volume of collected datasets.
- An intelligent treatment approach is needed to perform effective detection and diagnosis of fatty liver disease. It carried out the challenge of analyzing the multiple ultrasound images as those datasets are indeterminate nodules.
- The machine learning algorithms are to be applied to overcome the challenges of complex images of fatty liver disease with lesser / average quality and perform analysis.
- Based on fatty liver disease existence, there are few challenges mentioned below,
 - Accurate diagnosis based on the image datasets of fatty liver disease and perform precise decision making.
 - A reliable way of identifying the disease at the appropriate time during the treatment process of identification and diagnosis.

- Ability to extract the fatty liver disease image effectively as it is based on behavior of the patient and diagnostic results.

III. Problem Statement

As patient health data is a concern, the heterogeneity problem on data occurs during data extraction and prediction. It also overcomes the problem of improper data accessibility as it needs to be mitigated for the patient's data related to healthcare. Here we need an automated framework of Machine learning. Considering the heterogeneity problem helps to improve the evaluation of patient monitoring through patient care metrics like cost and staying length, which also enhances the patient treatment process. The issue of heterogeneity is considered in the data processing to extract the data through specific rules to form another representation of data.

IV. Proposed Model

The main objective of this work is to provide enhanced health monitoring based on data aggregation and using prediction-based learning algorithms for health care applications.

- Designing the intelligent-based learning framework helps to improve the caring for the patient by in-time doctor's diagnosis and reduce the cost concerning the monitoring and resource usage.
- The modified random forest integrated with the decision tree helps to perform an effective prediction process. It will predict liver disease using the ultrasound image by coming to the variation problem in the datasets feature.
- The modified forecast model based on machine learning as it avoids the prognosis problem.
- Fatty liver disease classification is proposed based on the feature identification using the image dataset and improve the accuracy and treatment process by overcoming the problem of time complexity and response time.

As data intelligence is growing vastly in health care and intelligent appliance, there is a vast amount of data to be analyzed using big data. The artificial intelligence of automated processes plays a significant role in monitoring patient health care if the patient overcomes the problem of heterogeneity in the case of a large number of datasets, complexity as per the patient-specific metrics, and overcome the problem of accessing the data effectively.

Based on the health care application, the information's are obtained from the IoT devices in the process, and those data are extracted out structurally. Those data are sent to the doctors, and the prediction-based learning process is applied and those process helps to diagnose the treatment in an earlier stage. Here we propose the automated framework with the integration of AI and IoT. Considering the heterogeneity problem helps improve the evaluation of patient monitoring through patient care metrics like cost and staying length, which also enhances the patient treatment process. Thus, the evaluation is done on the parameters related to disease health care about data scalability and flexibility.

V. Research Methodology:

Here, the modified random forest integrated with C 4.5 algorithm is proposing as it considers the datasets as input by creating several subtrees with random variables 'V'. The subtree creation is done for 'n' number of trees along with the leaf node. The analysis is done on the proposed work related to data aggregation and scalability of data based on datasets; it will perform better than the existing algorithms like Apriori algorithm, Decision Trees, etc. The proposed work algorithm will perform effectively related to the above parameter with some more modification as needed during the implementation.

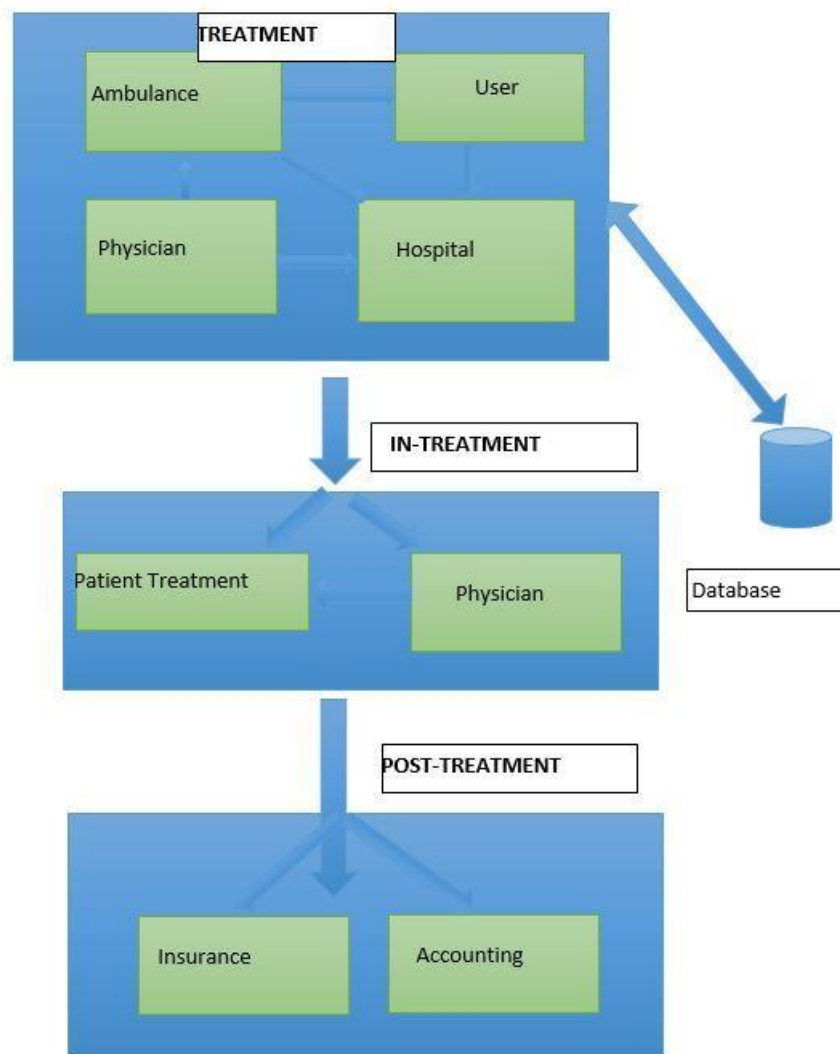


FIG. 1. PROPOSED FRAMEWORK

V.1. Learning Process:

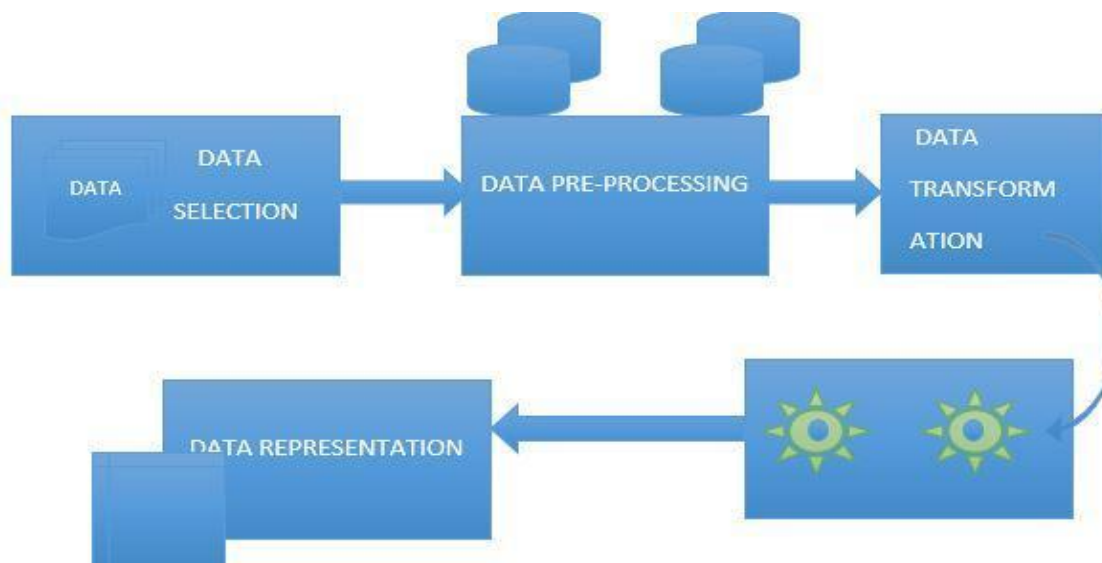


FIG. 2. DATA EXPLORATION

V.2. PREDICTION PHASE:

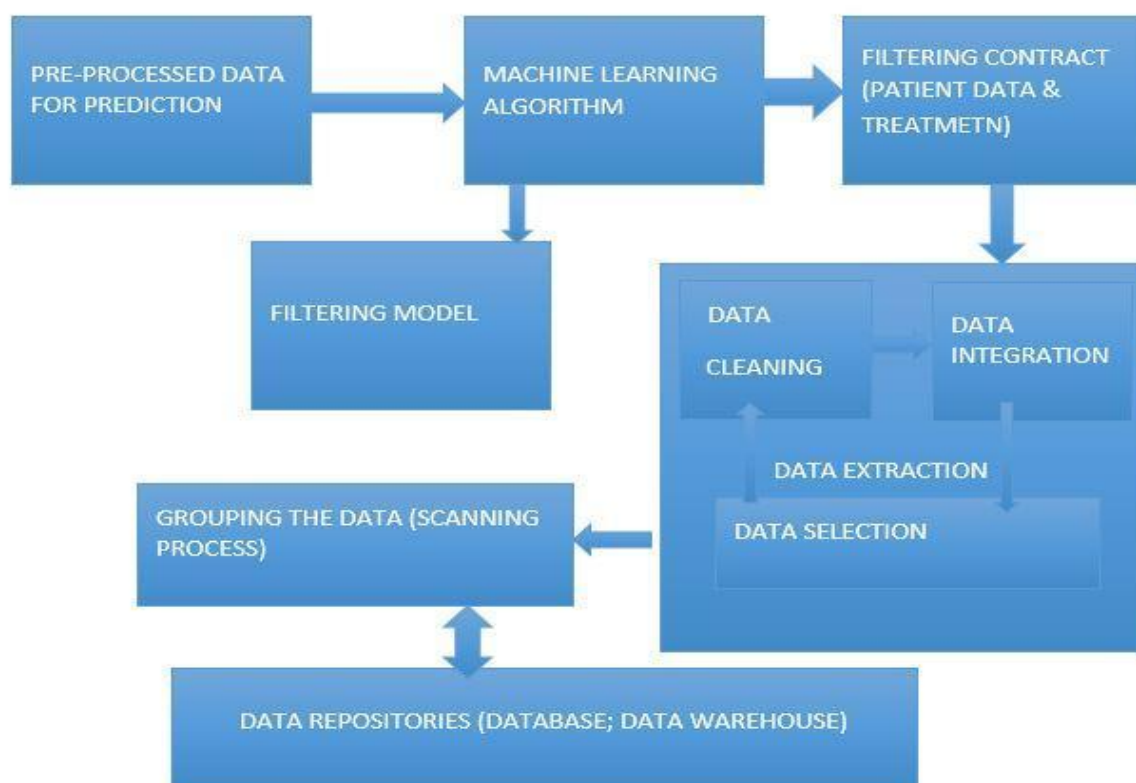


Fig. 3. PREDICTION MODEL

ALGORITHM 1: MODIFIED PREDICTION MODEL:

Input: Data training and testing

Output: Data Prediction

Modified Random Forest with the integration of C 4.5 Tress

 Compute the Coefficient of the training Model.

 Applying Sigmoid Function

 Processing the data mapping Process

 Mapping Between the training and testing data

 Deploying Data Clustering

 Determining the Data prediction

ALGORTIHM 2: MODIFIED RANDOM FOREST ALGORITHM:

Input: Datasets

Output: Binary Tree

Initialize

 Tree 'T' been selected to derive Sub Tree

 Collecting of Data' Subset 'S''

 For Subset to initialize 1 to 'n' Tree

 Train the data

 Construct the data samples with 'N' Size

 Terminate when node has limited value

 Select the random variables 'V' from Sample' S'

 Based on Node, tree to be spitted into several subtree with 'n' leaf node

 Generate random tree

Stop

As data intelligence is growing vastly in health care and intelligent appliance, there is a vast amount of data to be analyzed using big data. The Machine Learning of automated processes plays a significant role to carry out the process of monitoring patient health care. So, usually the patient overcomes the problem of variation in the more considerable dataset number and complexity as per the patient-specific metrics and overcomes the problem of accessing the data effectively.

Based on the health care application, we propose the intelligent-based learning framework integrated with machine learning to improve the evaluation of patient monitoring through patient care metrics like data accuracy, cost and time complexity. It also enhances identifying

and monitoring liver disease as the patient treatment process. Thus, the evaluation is done on the parameters related to disease of health care about data scalability and flexibility.

In the future, advanced learning algorithms can be deployed to perform against the prediction on the early treatment diagnosis for other liver disease diseases. Other than disease, it can also be deployed on the complex image generation on various critical diseases as time complexity can also be reduced further.

VI. Performance Analysis

As data intelligence grows in health care and intelligent appliances, there is an increasing amount of data to be examined utilizing big data. An important part of carrying out the process of monitoring patient health care is machine learning. Therefore, according to patient-specific measures, the patient typically overcomes the challenge of variance in the more significant dataset number and complexity and efficiently obtaining the data.

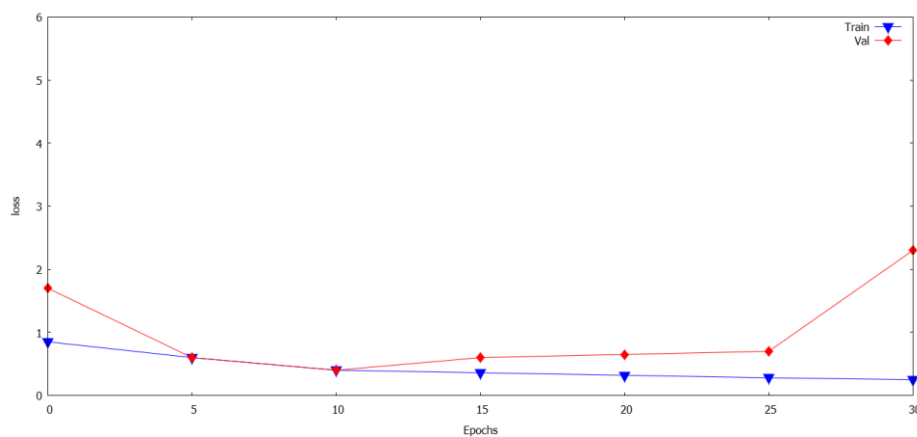


Figure 4. Epochs Vs Loss

As phases increase from 0 to 30, accuracy increases. Figure 5 depicts it.

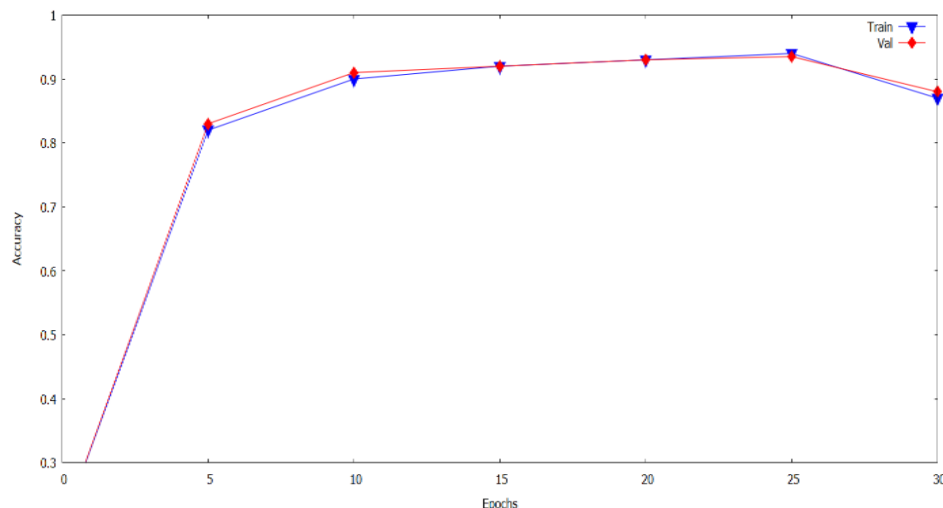


Fig 5. Epochs Vs Accuracy

We provide an intelligent learning framework that is combined with machine learning, based on the health care application, to enhance the assessment of patient monitoring using patient care metrics including data correctness, cost, and time complexity. As the patient treatment procedure consists of

three phases—pre-treatment, in-treatment, and post-treatment—it also facilitates the detection and monitoring of cancer. Thus, the characteristics linked to breast cancer health care data scalability and adaptability are evaluated.

By changing the epochs from 0 to 30, Figure 4 computes the loss using the categorization model. Saturation of the loss occurs as the recommended value increases across epochs.

Different loss function models, such as focal_tversky and categorical_crossentropy, are used in Figures 6 and 7. The accuracy is determined by comparing the suggested Res U-Net to the present one and changing iterations. The precision increases with iterations. For the loss function depicted in Figure 6, this is specific to focal_tversky. Category_cross entropy for the loss function is shown in Figure 7.

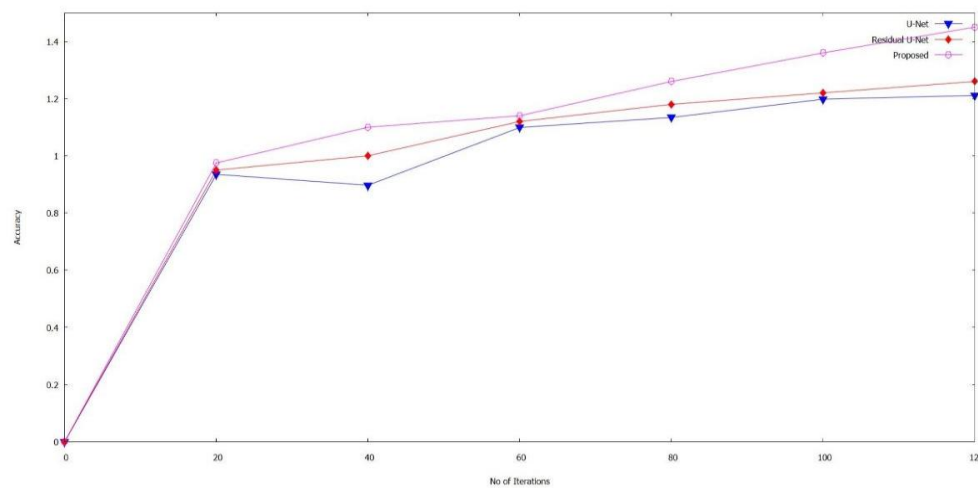


Fig 6. No of iteration Vs Accuracy (Loss Function: focal_tversky)

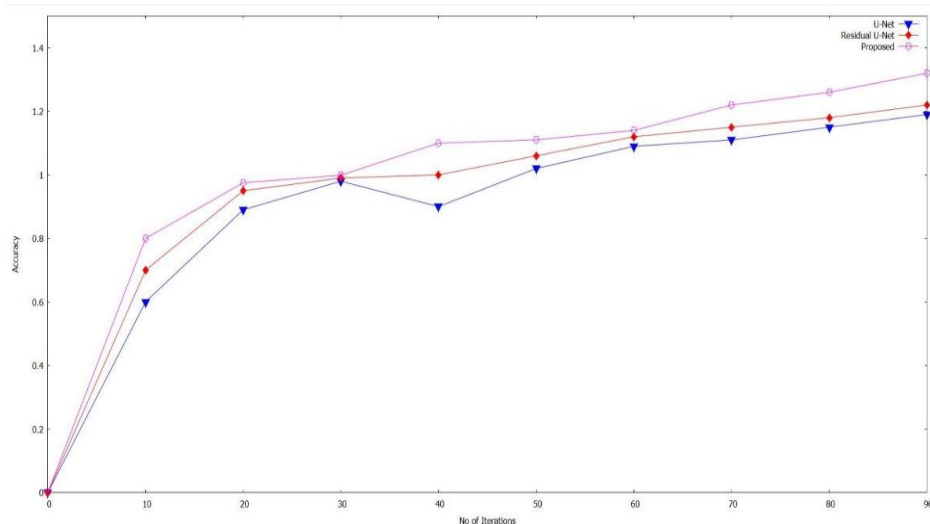


Fig 7. No of iteration Vs Accuracy (Loss Function: categorical_crossentropy)

VII. Conclusion

Within the scope of this work, the machine learning algorithm contributes to the successful execution of the identification process as well as the treatment process. Based on the statistics pertaining to fatty liver disease, there are several research gaps that have been identified. It is

possible that there is a more significant fluctuation in the data. The patient receives an incorrect diagnosis as a consequence of this, which leads to the problem of heterogeneity overall. There is an issue with prognosis that arises during the process of prediction, which ultimately results in the occurrence of disease more frequently in the future. The process of identifying the liver requires a significant amount of time and response, which will have an impact on the therapy that is administered in a timely manner and will lead to a high level of complexity in the treatment process for fatty liver disease.

Due to the fact that it requires some alterations, the framework that has been provided is not applicable to any other liver disease ailment. This article will discuss the limits of the research that pertain to the analysis of the complicated dataset of ultrasound pictures. The research needs to be effective since it requires a classification method for fatty liver disease. There is a direct correlation between the restrictions of time complexity occurrence and the outcome of the prediction procedure.

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