Efficient Hybrid CNN Method to Classify the Liver Diseases

Venugopal Reddy Modhugu[1*]

[1*] Senior Member of Technical Staff, Oracle, Virginia, USA.
venugopalreddymodhugu@gmail.com, Orcid: https://orcid.org/0000-0001-8078-5650

Received: May 13, 2023; Accepted: June 26, 2023; Published: September 30, 2023

Abstract

This study focuses on classifying liver diseases using dynamic CT scan images and deep learning techniques. The primary objective is to develop accurate and efficient models for distinguishing between different liver disease categories. Three deep learning models, ResNet50, ResNet18, and AlexNet, are employed for three-class classification, including Hepatitis/cirrhosis, Hepatitis/Fatty liver, and Hepatitis/Wilson's Disease. The dataset comprises dynamic CT scan images of the liver, each manually segmented to identify lesions. To enhance model performance, the data is pre-processed by resizing, normalization, and data augmentation. The dataset is split into training, validation, and test sets for model evaluation. The performance of each model is assessed using confusion matrices, accuracy, sensitivity, and specificity. Results show varying accuracies for different liver disease classes, indicating the strengths and limitations of the models. To overcome the limits of the three-class classifiers, a framework for the Efficient Hybrid CNN method to classify Liver diseases (EHCNNLD) is proposed, combining the predictions from the three models with weighted probabilities. The Proposed EHCNNLD method demonstrates improved accuracy and classification power, enhancing the overall performance for liver disease classification. The study highlights the potential of deep learning techniques in medical image analysis and clinical diagnosis. The findings provide valuable insights into developing robust and accurate models for liver disease classification, paving the way for medical research and patient care advancements.

Keywords: Liver Disease, Hybrid CNN, Metabolism, Deep Learning, Fully Convolutional Network, Classification.

1 Introduction

The liver plays a vital role in metabolism, detoxification, and synthesizing essential substances, making it a necessary organ for overall health. In recent years, dietary habits, working environment, and balanced living have changed, making liver illness the most frequent. Liver illnesses impair the liver's structure and function, causing numerous health difficulties. Symptoms, causes, and treatments vary for liver illnesses (Aggarwal, Shreve, et al., 2021; Janjua et al., 2017).

Liver disease diagnoses and classifications are divided into hepatitis, cirrhosis, fatty liver disease, liver cancer, etc. Viruses (hepatitis A, B, C, D, and E), alcohol, medicines, toxins, and autoimmune diseases may cause liver inflammation or hepatitis. Cirrhosis is the late stage of liver scarring (fibrosis), usually induced by chronic hepatitis or heavy alcohol usage. People who don't consume alcohol may develop Non-Alcoholic Fatty Liver Disease (NAFLD) (Aggarwal, Shreve, et al., 2021; Hectors et al., 2021). It's linked to obesity, diabetes, and metabolic syndrome. Alcoholic liver disease comprises fatty

Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications (JoWUA), volume: 14, number: 3 (September), pp. 36-47. DOI: *10.58346/JOWUA.2023.I3.004*

*Corresponding author: Senior Member of Technical Staff, Oracle, Virginia, USA.

liver, alcoholic hepatitis, and cirrhosis (Ishizawa et al., 2022; Y. Liu et al., 2022; Łuczykowski et al., 2021). Metastatic liver cancer from other organs or primary liver cancer from liver cells may cause liver cancer. Bacterial or parasite infections may create a liver abscess, a pus-filled liver lesion (Singh et al., 2020; Valenzuela-Vallejo & Mantzoros, 2022; Ye et al., 2022). Copper accumulates in the liver and other organs in Wilson's disease, causing liver damage and neurological issues. Hemochromatosis is a genetic condition that causes excess iron absorption and deposit in several organs, including the liver. PBC, a chronic autoimmune disease, damages the liver's tiny bile ducts. PSC induces liver damage and cirrhosis by inflaming and scarring the bile ducts (X. Liu et al., 2017; X. Zhang et al., 2021).

2 Literature Survey

Traditional Approaches

Traditional approaches to detecting liver diseases typically involve a combination of medical history assessment, physical examination, laboratory tests, and medical imaging (Chassagne et al., 2018; Ma et al., 2023). The initial step in diagnosing liver disease consists in taking a detailed medical history, including any symptoms, family history, and risk factors for liver disease (Nowak et al., 2021; Zheng et al., 2019). A physical examination may be conducted to check for signs of liver enlargement or tenderness. Various blood tests assess liver function and identify liver damage or dysfunction markers. These tests may include liver function tests (LFTs) to measure liver enzymes, bilirubin levels, albumin, and other liver-related features. Medical imaging techniques help visualize the liver and detect abnormalities. Standard imaging methods include Ultrasound, Which is non-invasive and widely used to assess liver structure and identify tumors, cysts, or signs of cirrhosis (Acharya et al., 2015; Alivar et al., 2016; Saba et al., 2016). Computed Tomography (CT) scan provides detailed cross-sectional images of the liver, aiding in detecting tumors and other liver conditions (X. Zhang et al., 2021). Magnetic Resonance Imaging (MRI) offers high-resolution images of the liver and surrounding organs, helping to diagnose liver diseases more accurately (Hectors et al., 2021; Nowak et al., 2021). FibroScan or transient elastography Measures liver stiffness to assess fibrosis or cirrhosis. In some cases, a liver biopsy may be performed to obtain a small sample of liver tissue for microscopic examination (Shu et al., 2019). This can help determine the cause and severity of liver disease, particularly in cases where the diagnosis remains uncertain after other tests. When liver disease is suspected to be caused by viral infections such as hepatitis B or C, specific blood tests are conducted to detect the presence of viral antigens or antibodies. Blood tests can also check for specific antibodies associated with autoimmune liver diseases like autoimmune hepatitis or primary biliary cirrhosis (Goyal et al., 2022). Alcohol and toxicology screening, for individuals with a history of alcohol abuse or exposure to toxins, screening for alcohol or toxic substances in the blood may be performed (Aggarwal, Rozenbaum, et al., 2021; Park et al., 2022).

These traditional approaches are valuable; advances in medical technology and research have also led to the developing of more sophisticated and less invasive methods for detecting and diagnosing liver diseases. Additionally, a multidisciplinary approach involving hepatologists, gastroenterologists, radiologists, and pathologists is often employed to analyze accurately and recommend appropriate treatment options (Aggarwal, Shreve, et al., 2021; Baars et al., 2022; Cameron Wild et al., 2019).

Sensors Used to Detect Liver Diseases

These sensors aim to provide quicker, more accurate, and non-invasive methods of diagnosing and monitoring liver conditions. Some promising sensor technologies explored for liver disease detection include Biosensors, devices that combine a biological element (e.g., enzymes, antibodies, or receptors)

with a transducer to detect specific biological markers (Cheng et al., 2021). In the context of liver diseases, biosensors can be designed to detect liver function or damage biomarkers, such as liver enzymes, bilirubin, or specific proteins associated with certain liver conditions. Nanotechnology offers innovative ways to detect liver diseases at an early stage (Mojumder et al., 2022). Nanosensors can be engineered to target particular liver cells or biomarkers, providing sensitive and precise detection capabilities. Additionally, nanoparticles could deliver therapeutic agents directly to affected liver cells. Breath analysis is a non-invasive approach that can detect liver diseases. Liver-related volatile organic compounds (VOCs) can be measured in a person's breath, providing valuable information about their liver health. These breath analyzers are often portable and could be used for early-stage screening. Microfluidics involves the manipulation of tiny amounts of fluid in microchannels (Wahba et al., 2023; Yang et al., 2022). Microfluidic devices are being explored for liver disease detection as they can analyze small blood samples and assess liver function markers efficiently. Integrating sensor technology with smartphones can offer a convenient and accessible way to monitor liver health. Smartphone apps combined with external sensors or attachments could enable users to track specific liver function parameters regularly. Electrochemical sensors can detect particular biomarkers related to liver diseases through changes in electrical properties when in contact with target substances. The field of sensor technology is continually evolving, and there may have been further advancements beyond my last update. Additionally, while these sensors show promise, not all might be readily available or approved for clinical use. Proper validation and regulatory approvals are necessary before widespread implementation in clinical settings (Cheng et al., 2021; Gatos et al., 2017; Wolfe et al., 2012; Xu, 2021).

Computational Intelligence

Computational methods have gained considerable importance in detecting and diagnosing liver diseases. By harnessing the power of artificial intelligence, machine learning, and data analytics, these methods enable in-depth analysis of medical data, identifying patterns, and making accurate predictions related to liver disease diagnosis. Integrating these advanced technologies has significantly enhanced the medical field's ability to effectively assess and understand liver diseases, improving patient care and better outcomes. Some computational approaches used to detect liver diseases include Machine learning algorithms that can be trained on large datasets of medical records, laboratory results, and imaging data to recognize patterns associated with different liver diseases. These algorithms can then be used to classify new patient data and assist in diagnosing specific liver conditions (Abdar et al., 2017; Haas et al., 2021; X. Liu et al., 2017). Deep learning, a subset of machine learning, involves using neural networks with multiple layers to learn complex representations from data. Convolutional neural networks (CNNs) have been applied to medical imaging, including CT scans and MRI images of the liver, to aid in detecting liver tumors, fibrosis, and other abnormalities. Computational methods can automatically identify relevant features or biomarkers from complex datasets that are indicative of liver disease. These features can then be used in diagnostic models or as early warning indicators. Combining data from various sources, such as clinical data, laboratory results, medical imaging, and genetic information, can enhance the accuracy and reliability of liver disease detection and diagnosis (Ahad et al., 2023; Cheng et al., 2021; Yue et al., 2023).

Predictive modeling can be used to forecast disease progression, risk of complications, or treatment outcomes based on patient characteristics and historical data. Natural Language Processing (NLP) techniques can be employed to analyze unstructured medical text data, such as electronic health records and medical literature, to extract relevant information related to liver diseases and aid decision-making (Donnelly et al., 2022; Redman et al., 2017). Support Vector Machines (SVM) is a supervised learning algorithm that can classify patients into different liver disease categories based on their clinical features.

Rule-based systems use a set of defined rules and logic to analyze patient data and arrive at diagnostic conclusions. Network-based approaches can be used to study the interactions between genes, proteins, and other molecular factors associated with liver diseases, helping to identify potential drug targets and pathways involved in the disease process. Ensemble methods combine multiple machine learning models to improve accuracy and reduce overfitting, which can benefit liver disease diagnosis in complex cases. computational methods hold great promise in the field of liver disease detection. They are not meant to replace traditional diagnostic approaches but complement and enhance them. Integrating computational methods with clinical expertise can lead to more precise and personalized diagnoses, improving patient care and treatment outcomes (Bonah et al., 2020; P & G, 2022; L. Zhang et al., 2022).

Deep learning is used to classify liver state, such as cirrhosis or non-cirrhosis, using dynamic ultrasound pictures. To differentiate liver pictures, two-class (Hepatitis/cirrhosis, Fatty liver, Wilson's Disease, etc.) or three-class (Alcoholic liver disease/cirrhosis/Liver cancer) classifiers were trained. Next, a hybrid classifier is developed that uses a majority voting technique to aggregate the weighted probabilities of each classifier's classifications (Hectors et al., 2021; Huang et al., 2023; Nowak et al., 2021; Pasyar et al., 2021; Shaheen et al., 2023).

3 Proposed Method

Liver disease classification using CT scan images is a significant area of research and can improve the accuracy and early detection of liver conditions. Several machine learning and deep learning techniques have been applied to this task with promising results (Bae, D., 2021). A general outline of the Efficient Hybrid CNN method to classify liver diseases (EHCNNLD) proposed method or process:

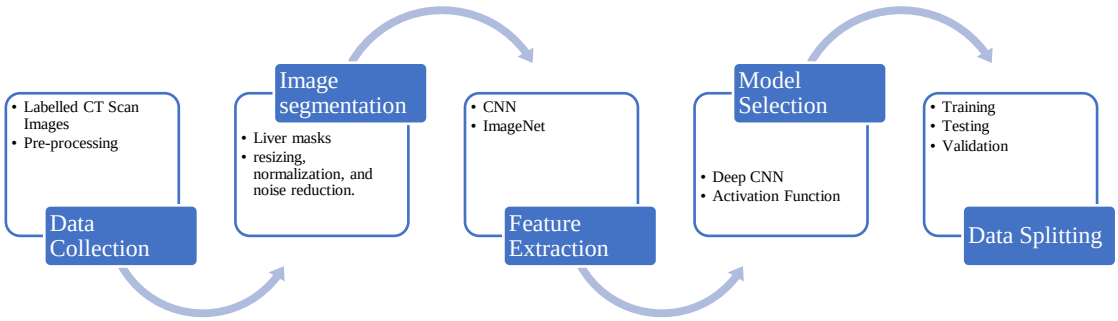

Figure 1: Proposed Method Framework for Efficient Hybrid CNN Method to Classify the Liver Diseases (EHCNNLD)

Data Collection and Preprocessing: Obtain a large dataset of CT scan images with labeled ground truth indicating the presence or absence of liver disease. Preprocess the images to standardize their size, orientation, and intensity levels to ensure consistency. LiTS (Liver Tumor Segmentation Challenge) Dataset: The LiTS dataset contains 201 CT scans of the liver with manually segmented lesions. It was part of a challenge for liver tumor segmentation but can also be used for liver disease classification tasks. The dataset is available at: https://competitions.codalab.org/competitions/17094.

Image Segmentation: For more targeted analysis, perform liver segmentation to isolate the liver region from the rest of the image. Accurate segmentation is crucial for focusing the analysis on the liver area. Gather a dataset of medical images e.g., CT scans) with ground truth liver segmentation masks.

These masks indicate the exact pixels or regions corresponding to the liver in each image. The dataset should include both photos and their corresponding segmented liver masks. Preprocess the images to ensure uniformity in size, orientation, and intensity levels. Common preprocessing steps include resizing, normalization, and noise reduction. Utilize semantic segmentation models that can classify each image pixel into different classes. In this case, the classes would be "cirrhosis" or "non-cirrhosis" regions. Convolutional Neural Networks (CNNs), particularly ResNet-50, have performed excellently in medical image segmentation tasks.

Feature Extraction: Extract relevant features from the segmented liver images to represent the characteristics of different liver diseases. In the context of liver disease detection, a wide range of features can be utilized, including texture descriptors, shape features, intensity histograms, or deep features learned from pre-trained convolutional neural networks (CNNs). This study focused on CNN feature selection, which involves leveraging the power of transfer learning. By utilizing pre-trained CNN models on large image datasets like ImageNet, valuable features can be extracted from the intermediate layers of the CNNs. These extracted features serve as higher-level representations of the input images, contributing to more effective and accurate liver disease classification.

Model Selection: In selecting an appropriate classification model for the given dataset's size and complexity, we have several standard options, including support vector machines (SVM), random forests, gradient boosting machines (GBM), and deep learning-based convolutional neural networks (CNNs). For this study, we have used a Deep CNN as the classification model.

A Deep Neural Network (DNN) is an artificial neural network composed of multiple layers of interconnected neurons or nodes. The term "deep" refers to its structure, which typically involves several hidden layers between the input and output layers. DNNs have gained tremendous popularity and achieved remarkable success in various domains, including image recognition, natural language processing, and medical image analysis. The key to their effectiveness lies in their ability to learn hierarchical representations from complex data, enabling them to capture intricate patterns and features in the dataset. Thus, a Deep CNN is an ideal choice for handling the complexities of the liver disease classification task in this study.

In Figure 2, the Input represents the medical image data fed into the DNN. The DNN consists of multiple Hidden Layers (typically two or more) where each layer comprises interconnected neurons or nodes. Each neuron in the hidden layers processes the output from the previous layer by applying weights and biases, followed by an activation function.

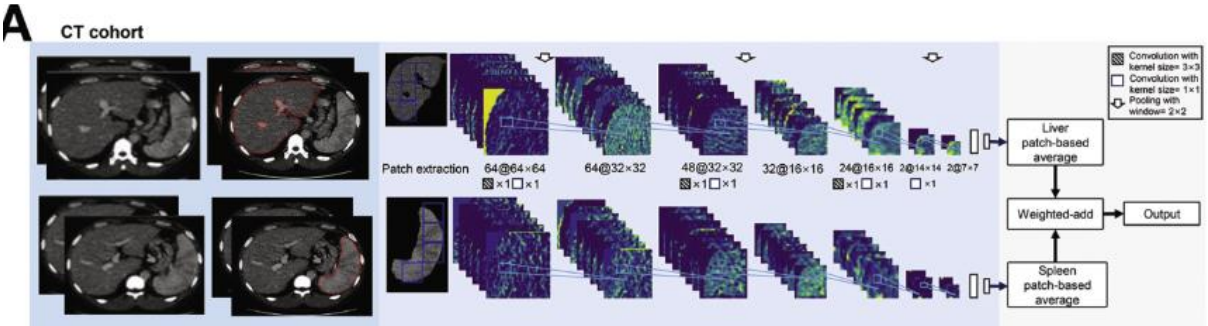

Figure 2: Deep Neural Network for Liver Disease

Figure 2 shows the data flow through the hidden layers, and at the end, the final layer is the Output Layer. In the context of liver disease detection, the output layer will have neurons representing different disease categories (e.g., cirrhosis, non-cirrhosis, Hepatitis, liver cancer etc.). The network output will be

the probabilities or scores associated with each class, indicating the likelihood of the input image belonging to a particular liver disease category.

Training and Validation: Split the dataset into training and validation sets. Use the training set to train the chosen model and tune hyperparameters for optimal performance. Validate the model's performance on the validation set to avoid overfitting. Training and validation are essential in building and evaluating machine learning models, including Deep Neural Networks (DNNs), for detecting liver disease from medical images. These steps help ensure the model learns meaningful representations from the data and generalizes well to new, unseen data. Before initiating the training process, the dataset is divided into three subsets: the training set, the validation set, and the test set. The training set is utilized to train the model, allowing it to learn from the data. The validation set is employed to fine-tune hyperparameters and assess the model's performance during the training phase, helping to prevent overfitting. Lastly, the test set is used to evaluate the final model's performance on unseen data, providing an unbiased measure of its effectiveness and generalization capability.

Testing and Evaluation: Testing and evaluation are crucial steps in the machine learning workflow to assess the performance of a trained Deep Neural Network (DNN) model for liver disease detection. These steps involve using the model to make predictions on a separate test dataset containing data the model has yet to see during training or validation. The evaluation metrics help determine how well the model generalizes to new, unseen data. The test dataset is an independent subset of the original data set aside at the beginning and not used during training or validation. It serves as a final evaluation benchmark for the trained DNN model. Assess the trained model's performance on a separate test set not used during training or validation. Evaluate the model's accuracy, precision, recall, F1-score, confusion matrix, and AUC-ROC to measure its classification performance. The trained DNN model is applied to each sample in the test dataset to predict the likelihood of the selection belonging to different liver disease categories.

Proposed Algorithm for Efficient Hybrid CNN method to classify Liver diseases (EHCNNLD):

Algorithm for EHCNNLD

Step 1: Load and Preprocess Data

Load dynamic CT scan images of the liver with manually segmented lesions

Preprocess the images (e.g., resize, normalization, data augmentation)

Step 2: Split Data into Training, Validation, and Test Sets

Split the preprocessed data into training (80%), validation (10%), and test (10%) subsets

Step 3: Build Deep Learning Models

Define the architecture of ResNet50, ResNet18, and AlexNet for liver disease classification

Compile the models with appropriate loss functions and optimizers

Step 4: Train Three-Class Classifiers

Train the ResNet50, ResNet18, and AlexNet models for three-class classification

Monitor training progress and performance on the validation set

Step 5: Evaluate Three-Class Classifiers

Assess the performance of each model using confusion matrices, accuracy, sensitivity, and specificity

Step 6: Build Hybrid Classifier

Develop a hybrid classifier by combining the results from ResNet50, ResNet18, and AlexNet

Assign weights to each model's predictions for ensemble classification

Step 7: Train Hybrid Classifier
Train the hybrid classifier using the weighted probabilities from the three-class classifiers
Monitor training progress and performance on the validation set
Step 8: Evaluate Hybrid Classifier
Assess the performance of the hybrid classifier using confusion matrices and accuracy
Step 9: Compare Results
Compare the performance of the three-class classifiers and the hybrid classifier
Analyze accuracy, sensitivity, and specificity for each liver disease class
End of Algorithm

4 Implementation

This study developed four classifiers to categorize liver images as "cirrhosis" or "non-cirrhosis." The first three classifiers were explicitly designed to distinguish between different liver diseases, such as Hepatitis/cirrhosis, Hepatitis/Fatty liver, and Hepatitis/Wilson's Disease. The fourth classifier focused on classifying CT liver images into three categories: Hepatitis/cirrhosis/Liver cancer and Alcoholic liver disease/cirrhosis/Liver cancer. The results of the study indicated that the two-class classifiers exhibited superior performance compared to the three-class classifiers, which lacked sufficient classification power. To overcome this limitation, a EHCNNLD was proposed, which combined the outputs of all four trained classifiers. This EHCNNLD approach utilized weighted probabilities obtained from the softmax output layer of each classifier, enabling the assignment of probabilities to all classes for every input data point. By leveraging the strengths of each individual classifier, the hybrid classifier aimed to enhance the overall classification performance and provide more accurate and reliable predictions for liver disease classification.

In order to determine the most suitable weights for each classifier's output, a grid search approach was employed, spanning weight values from 0 to 1 with a step size of 0.112. The selection of the best configuration was based on the classification performance achieved. To ensure proper normalization of the weights, each optimal weight was divided by the total sum of all weights. Introducing the EHCNNLD approach aimed to significantly improve the overall classification performance while effectively addressing the complexities associated with multi-class classification. By integrating the strengths of individual classifiers, the hybrid EHCNNLD approach sought to provide more robust and accurate results for liver disease classification.

This section evaluated the classification performance of two liver status types: cirrhosis and non-cirrhosis. The evaluation process centered on utilizing dynamic CT scan images and deep learning techniques. The study utilized a dataset comprising 201 CT scans of the liver, each subjected to manual segmentation of lesions examinations. The liver images were subsequently categorized into three classes based on image specimens. The dataset was randomly split into training (80%) and validation (20%) sets. An illustrative example from Figure 3 showcased the training progress of ResNet50 with the modified Fully Convolutional Network. During training, 80% of the original dataset was utilized for training and augmentation, while the remaining 20% was dedicated to validation without any boost. Monitoring the training progress in deep learning proved beneficial, facilitating the evaluation of the network's accuracy improvement rate and aiding in the detection of potential issues such as local minimums or overfitting to the training data.

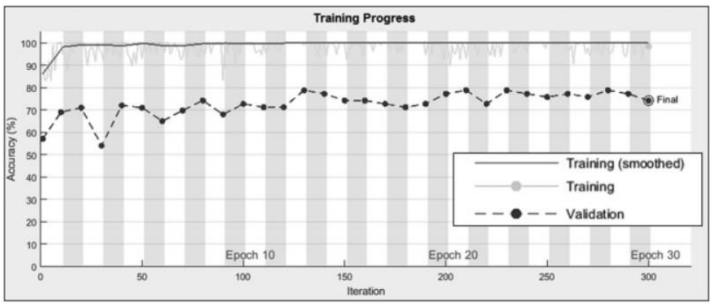

Figure 3: The Result of the Training Process

Figure 3 shows ResNet50's training and testing results for liver status classification from CT scan images using the planned Fully Convolutional Network (FCN). The training process utilized 80% of the data, while the remaining 20% was dedicated to validation without any boost and for classifying the CT images into 3 clusters, train the anticipated EHCNNLD approach. The performance of well-known networks such as ResNet50, ResNet18, and AlexNet for the 3-class classification is presented in Table 2. Additionally, Table 1 provides the appropriate investigative results for the 2-class classifiers using the aforementioned networks.

Figure 4 illustrates the confusion matrices, presenting the difference between Hepatitis/cirrhosis, Hepatitis/Fatty liver, and Hepatitis/Wilson's Disease using ResNet50. Furthermore, the investigational outcomes of the EHCNNLD approach are outlined in Table 2.

Table 1: Metrics Between Hepatitis/Cirrhosis, Hepatitis/Fatty Liver, and Hepatitis/Wilson's Disease

Methods	Sets	Accuracy	Sensitivity	Specificity
Resnet50	Hepatitis/cirrhosis	89.5%	91.9%	85.4%
	Hepatitis/Fatty liver	87.7%	91.9%	82.8%
	Hepatitis/Wilson's Disease	89.8%	99.99%	76.3%
ResNet18	Hepatitis/cirrhosis	87.5%	89.9%	85.2%
	Hepatitis/Fatty liver	85.0%	78.3%	91.4%
	Hepatitis/Wilson's Disease	94.5%	89.8%	94.3%
AlexNet	Hepatitis/cirrhosis	83.1%	92.5%	78.4%
	Hepatitis/Fatty liver	84.5%	94.4%	76.2%
	Hepatitis/Wilson's Disease	86.3%	92.8%	78.5%

Table 2: Performance of the Various Networks for Classifying the Proposed Method EHCNNLD

Methods	Accuracy of 3 class classifier	Accuracy of EHCNNLD
ResNet50	80.7%	87.5%
ResNet18	76.4%	84.9%
AlexNet	78.3%	85.6%

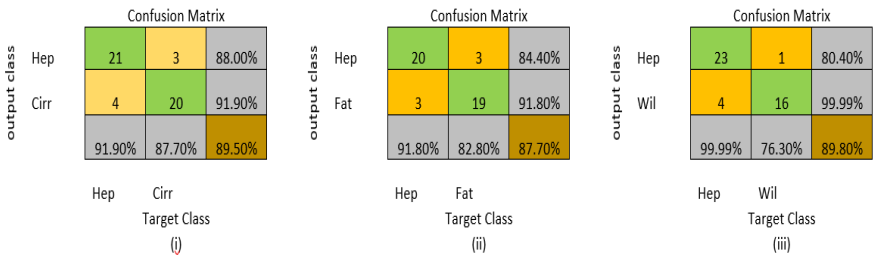

Figure 4: Confusion Matrices for Classifying Different Liver Conditions

Figure 4 illustrates the confusion matrices for classifying different liver conditions, including Hepatitis/cirrhosis, Hepatitis/Fatty liver, and Hepatitis/Wilson's Disease. These classifications were achieved using ResNet50 with Fully Convolutional Networks (FCN).

To evaluate the diagnostic performance of the classification results, the study utilized three essential metrics: "Sensitivity," "Specificity," and "Accuracy." These metrics are widely used in medical diagnostics and are defined as follows:

$$\text{Specificity} = \frac{TP}{TP+FN}$$

$$\text{Specificity} = \frac{TN}{TN+FP}$$

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

These confusion matrices help evaluate the classifiers' performance for different liver disease classifications. The high accuracy values indicate that the models have successfully classified most samples correctly for each specific class.

5 Conclusion

The study aimed to classify liver diseases using various deep-learning models. The results presented in the confusion matrices demonstrated the performance of the models for other output classes, including Hepatitis/cirrhosis, Hepatitis/Fatty liver, and Hepatitis/Wilson's Disease. The models achieved relatively high accuracy for classifying Hepatitis/cirrhosis, ranging from 80.40% to 91.90%. However, some misclassifications were observed in other classes, leading to slightly lower accuracy values. Notably, the model showed a remarkably high accuracy of 99.99% for classifying Liver cancer in the third confusion matrix. Overall, deep learning models, such as ResNet50, ResNet18, and AlexNet, demonstrated promising results in classifying liver diseases. The work shows deep learning's promise in medical picture analysis and illness identification.

However, the classification performance may vary based on the dataset, size, and complexity of liver diseases. Further research and refinement of the models are necessary to enhance their accuracy and generalizability. The study contributes valuable insights into applying deep learning for liver disease classification. It encourages future investigations to develop more robust and accurate models for medical image analysis and clinical diagnosis.

References

[1] Abdar, M., Zomorodi-Moghadam, M., Das, R., & Ting, I.H. (2017). Performance analysis of classification algorithms on early detection of liver disease. *Expert Systems with Applications, 67*, 239-251.

[2] Acharya, U.R., Faust, O., Molinari, F., Sree, S.V., Junnarkar, S.P., & Sudarshan, V. (2015). Ultrasound-based tissue characterization and classification of fatty liver disease: A screening and diagnostic paradigm. *Knowledge-Based Systems, 75*, 66-77.

[3] Aggarwal, M., Rozenbaum, D., Bansal, A., Garg, R., Bansal, P., & McCullough, A. (2021). Development of machine learning model to detect fibrotic non-alcoholic steatohepatitis in patients with non-alcoholic fatty liver disease. *Digestive and Liver Disease, 53*(12), 1669-1672.

[4] Aggarwal, M., Shreve, J., & McCullough, A. (2021). 587 Machine Learning Model Correctly Identifies Patients with Advanced Liver Fibrosis Which Are Indeterminate by Fib-4 Index in Non-Alcoholic Fatty Liver Disease. *Gastroenterology*, *160*(6), S-114.

[5] Ahad, M.T., Li, Y., Song, B., & Bhuiyan, T. (2023). Comparison of CNN-based deep learning architectures for rice diseases classification. *Artificial Intelligence in Agriculture, 9*, 22-35.

[6] Ahana, P., & Kavitha, G. (2022). Radiomic features based severity prediction in dementia MR images using hybrid SSA-PSO optimizer and multi-class SVM classifier. *IRBM*, *43*(6), 549-560.

[7] Alivar, A., Danyali, H., & Helfroush, M.S. (2016). Hierarchical classification of normal, fatty and heterogeneous liver diseases from ultrasound images using serial and parallel feature fusion. *Biocybernetics and Biomedical Engineering*, *36*(4), 697-707.

[8] Baars, T., Gieseler, R.K., Patsalis, P.C., & Canbay, A. (2022). Towards harnessing the value of organokine crosstalk to predict the risk for cardiovascular disease in non-alcoholic fatty liver disease. *Metabolism*, *130*.

[9] Bae, D., & Ha, J. (2021). Performance Metric for Differential Deep Learning Analysis. *Journal of Internet Services and Information Security (JISIS)*, *11*(2), 22-33.

[10] Bonah, E., Huang, X., Yi, R., Aheto, J.H., & Yu, S. (2020). Vis-NIR hyperspectral imaging for the classification of bacterial foodborne pathogens based on pixel-wise analysis and a novel CARS-PSO-SVM model. *Infrared Physics & Technology*, *105*.

[11] Chassagne, F., Haddad, M., Amiel, A., Phakeovilay, C., Manithip, C., Bourdy, G., & Marti, G. (2018). A metabolomic approach to identify anti-hepatocarcinogenic compounds from plants used traditionally in the treatment of liver diseases. *Fitoterapia*, *127*, 226-236.

[12] Cheng, N., Chen, D., Lou, B., Fu, J., & Wang, H. (2021). A biosensing method for the direct serological detection of liver diseases by integrating a SERS-based sensor and a CNN classifier. *Biosensors and Bioelectronics*, *186*.

[13] Donnelly, L.F., Grzeszczuk, R., & Guimaraes, C.V. (2022). Use of natural language processing (NLP) in evaluation of radiology reports: an update on applications and technology advances. In *Seminars in Ultrasound, CT and MRI*, *43*(2), 176-181. WB Saunders.

[14] Gatos, I., Tsantis, S., Spiliopoulos, S., Karnabatidis, D., Theotokas, I., Zoumpoulis, P., & Kagadis, G.C. (2017). A machine-learning algorithm toward color analysis for chronic liver disease classification, employing ultrasound shear wave elastography. *Ultrasound in medicine & biology*, *43*(9), 1797-1810.

[15] Goyal, T., Song, M.W., Moran, I.J., & Chen, V.L. (2022). Mo1381: An Automated Algorithm Accurately Identifies Cirrhosis Among Patients with Nonalcoholic Fatty Liver Disease (NAFLD), Including Those Without International Classification of Diseases (ICD) Codes for Cirrhosis or Elevated Fibrosis-4 scores. *Gastroenterology*, *162*(7), S-1238.

[16] Haas, M.E., Pirruccello, J.P., Friedman, S.N., Wang, M., Emdin, C.A., Ajmera, V.H., & Khera, A.V. (2021). Machine learning enables new insights into genetic contributions to liver fat accumulation. *Cell genomics*, *1*(3).

[17] Hectors, S.J., Kennedy, P., Huang, K.H., Stocker, D., Carbonell, G., Greenspan, H., & Taouli, B. (2021). Fully automated prediction of liver fibrosis using deep learning analysis of gadoxetic acid–enhanced MRI. *European radiology*, *31*, 3805-3814.

[18] Huang, H., Liu, Y., Xiong, Q., Xing, Y., & Du, H. (2023). A fatty liver diseases classification network based on adaptive coordination attention with label smoothing. *Biomedical Signal Processing and Control*, *86*.

[19] Ishizawa, S., Nishi, A., Kaifuchi, N., Shimobori, C., Nahata, M., Yamada, C., & Yamamoto, M. (2022). Integrated analysis of effect of daisaikoto, a traditional Japanese medicine, on the metabolome and gut microbiome in a mouse model of nonalcoholic fatty liver disease. *Gene*, *846*.

[20] Janjua, H.U., Andleeb, F., Aftab, S., Hussain, F., & Gilanie, G. (2017). Classification of liver cirrhosis with statistical analysis of texture parameters. *International Journal of Optical Sciences*, *3*(2), 18-25.

[21] Liu, X., Song, J.L., Wang, S.H., Zhao, J.W., & Chen, Y.Q. (2017). Learning to diagnose cirrhosis with liver capsule guided ultrasound image classification. *Sensors*, *17*(1), 1-11.

[22] Liu, Y., Zhou, B., Fu, H., Ding, X., Guo, W., & Li, M. (2022). Evidence-based research methods to evaluate the clinical curative effects of traditional Mongolian medicine—Gurigumu formulae for liver diseases as an example. *Pharmacological Research-Modern Chinese Medicine*, *2*.

[23] Łuczykowski, K., Warmuzińska, N., & Bojko, B. (2021). Current approaches to the analysis of bile and the determination of bile acids in various biological matrices as supportive tools to traditional diagnostic testing for liver dysfunction and biliary diseases. *TrAC Trends in Analytical Chemistry*, *142*.

[24] Ma, J.T., Xia, S., Zhang, B.K., Luo, F., Guo, L., Yang, Y., & Yan, M. (2023). The pharmacology and mechanisms of traditional Chinese medicine in promoting liver regeneration: A new therapeutic option. *Phytomedicine*, 1-14.

[25] Mojumder, S., Das, T., Das, S., Chakraborty, N., Saha, D., & Pal, M. (2022). Y and Al co-doped ZnO-nanopowder based ultrasensitive trace ethanol sensor: a potential breath analyzer for fatty liver disease and drunken driving detection. *Sensors and Actuators B: Chemical*, *372*.

[26] Nowak, S., Mesropyan, N., Faron, A., Block, W., Reuter, M., Attenberger, U.I., & Sprinkart, A. M. (2021). Detection of liver cirrhosis in standard T2-weighted MRI using deep transfer learning. *European radiology*, *31*(11), 8807-8815.

[27] Park, I., Kim, N., Lee, S., Park, K., Son, M.Y., Cho, H.S., & Kim, D.S. (2023). Characterization of signature trends across the spectrum of non-alcoholic fatty liver disease using deep learning method. *Life Sciences*, *314*.

[28] Pasyar, P., Mahmoudi, T., Kouzehkanan, S.Z.M., Ahmadian, A., Arabalibeik, H., Soltanian, N., & Radmard, A.R. (2021). Hybrid classification of diffuse liver diseases in ultrasound images using deep convolutional neural networks. *Informatics in Medicine Unlocked*, *22*.

[29] Redman, J.S., Natarajan, Y., Wang, J., Hanif, M., Feng, H., Kramer, J.R., & Kanwal, F. (2017). Utilizing Natural Language Processing (NLP) to Accurately Identify Fatty Liver Disease. *Gastroenterology*, *152*(5).

[30] Saba, L., Dey, N., Ashour, A.S., Samanta, S., Nath, S.S., Chakraborty, S., & Suri, J.S. (2016). Automated stratification of liver disease in ultrasound: an online accurate feature classification paradigm. *Computer methods and programs in biomedicine*, *130*, 118-134.

[31] Shaheen, H., Ravikumar, K., Anantha, N.L., Kumar, A.U.S., Jayapandian, N., & Kirubakaran, S. (2023). An efficient classification of cirrhosis liver disease using hybrid convolutional neural network-capsule network. *Biomedical Signal Processing and Control*, *80*.

[32] Shu, Z., Liu, W., Wu, H., Xiao, M., Wu, D., Cao, T., & Zhou, X. (2019). Symptom-based network classification identifies distinct clinical subgroups of liver diseases with common molecular pathways. *Computer methods and programs in biomedicine*, *174*, 41-50.

[33] Singh, J., Bagga, S., & Kaur, R. (2020). Software-based prediction of liver disease with feature selection and classification techniques. *Procedia Computer Science*, *167*, 1970-1980.

[34] Valenzuela-Vallejo, L., & Mantzoros, C.S. (2022). Time to transition from a negative nomenclature describing what NAFLD is not, to a novel, pathophysiology-based, umbrella classification of fatty liver disease (FLD). *Metabolism*, *134*.

[35] Wahba, M.E., Ayman, A., Zeid, A.M., Yasser, E.S., & Draz, M.E. (2023). Portable and green solid contact potentiometric sensor for the rapid and direct assay of clozapine in post-mortem rat liver and dosage forms: An analytical approach to forensic and pharmaceutical samples. *Microchemical Journal*, *186*.

[36] Wild, T.C., Koziel, J., Anderson-Baron, J., Hathaway, J., McCurdy, A., Xu, X., & Hyshka, E. (2019). Media coverage of harm reduction, 2000–2016: A content analysis of tone, topics, and interventions in Canadian print news. *Drug and alcohol dependence*, *205*.

[37] Wolfe, D., Gong, M., Han, G., Magee, T.R., Ross, M.G., & Desai, M. (2012). Nutrient sensor–mediated programmed nonalcoholic fatty liver disease in low birthweight offspring. *American journal of obstetrics and gynecology*, *207*(4), 1-11.

[38] Xu, J. (2021). Medical wireless sensor network coverage and clinical application of MRI liver disease diagnosis. *Microprocessors and Microsystems*, *81*.

[39] Yang, X., Xie, P., Liu, J., Han, X., Zhang, D., Ye, Y., & Zhao, Y. (2022). Dual-site fluorescent sensor for tracking lysosomal ATP and H2S during liver injury. *Chemical Engineering Journal*, *442*.

[40] Ye, J., Zhuang, X., Li, X., Gong, X., Sun, Y., Wang, W., & Zhong, B. (2022). Novel metabolic classification for extrahepatic complication of metabolic associated fatty liver disease: A data-driven cluster analysis with international validation. *Metabolism*, *136*.

[41] Yue, J., Yang, H., Feng, H., Han, S., Zhou, C., Fu, Y., & Yang, G. (2023). Hyperspectral-to-image transform and CNN transfer learning enhancing soybean LCC estimation. *Computers and Electronics in Agriculture*, *211*.

[42] Zhang, L., Zhang, Z., Wu, C., & Sun, L. (2022). Segmentation algorithm for overlap recognition of seedling lettuce and weeds based on SVM and image blocking. *Computers and Electronics in Agriculture*, *201*.

[43] Zhang, X., Nie, Y., Qiao, X., Li, K., Chen, W., & chen, Y.W. (2021). An Automatic Grading Method of Liver Cirrhosis from Abdominal CT Images. *In 3rd International Conference on Intelligent Medicine and Image Processing*, 57-62.

[44] Zheng, L., Wang, Y., Hemanth, D.J., Sangiah, A.K., & Shi, F. (2019). Data augmentation on mice liver cirrhosis microscopic images employing convolutional neural networks and support vector machine. *Journal of Ambient Intelligence and Humanized Computing*, *10*, 4023-4032.

Author Biography

Venugopal Reddy Modhugu, Senior Member of Technical staff, Oracle, VA USA, venugopalreddymodhugu@gmail.com, Orcid: https://orcid.org/0000-0001-8078-5650. He is a highly skilled Software Engineer with a master's degree in Computer Science. He has substantial experience in building IaaS platforms for edge cloud computing, designing distributed microservices architecture for backend systems, and developing data pipelines. His research interests include machine learning, edge cloud computing, and big data analysis. As a valuable asset for any software development team, he brings expertise and innovation to the field of Computer Science.