

A Multimodal Deep Learning Approach for Advancing Liver Disease Diagnosis and Prognosis Prediction

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Abstract- Using a multimodal deep learning framework, we have demonstrated the possibility to predict liver disease subtyping and prognosis with high accuracy. The framework includes over 1600 patients, for which medical imaging and clinical data have been collected. Convolutional Neural Networks (CNNs), Recurrent Neural Network (RNNs), and Long short-term memory (LSTMs) have been combined in the work to extract features from the input data and demonstrate correlation between input and output and model complexity. Such an approach allowed analyzing images and predicting liver diseases based on structural abnormality analysis with the use of CNNs. RNNs and LSTMs, in their turn, allowed combining features for multimodal data source analysis and sequential clinical data analysis providing information about patient history. The obtained results were accurate for each feature extraction and modeling, with the best performance demonstrated by CNN with RNN where the accuracy was 97.8% and another CNN with LSTM where the accuracy was around 94.5%. The model proved to be feasible and accurate in the context of its application to hepatology since multiple data sources were combined in the work. This approach allows accounting for all modes of data source and offers a comprehensive assessment including disease diagnosis and prognosis. The obtained results can be also applied to clinical practice where doctors can add data about their patients to receive more information on diagnosis or prognosis for better decision-making. Finally, the idea to use a multilayered feature from multimodal data sources can be transferable to other types of sequential and structural data and applied to other diseases for their diagnosis and prognosis. However, it is essential to test the framework in other settings to refine it or find limitations to its application.

Keywords— Liver disease, Multimodal, Deep learning, Subtyping, Prognosis prediction

I. INTRODUCTION

Liver disease represents a severe global health problem, the diverse etiologies and numerous clinical manifestations of which require accurate diagnosis and prognosis prediction for effective therapy [1], [2]. Defining the nature and severity of hepatic pathologies is traditionally based on the analysis of a single data modality, be it medical images of organs or

general clinical information, leading in many cases to inaccurate and incomplete insights. Consequently, the field of hepatology can benefit greatly from the application of multimodal deep learning frameworks developed to facilitate the simultaneous analysis of various data resources and enhance predictive value. Defined as models of deep learning based on multiple heterogeneous data sources, such frameworks are designed to pool information inferred from each modality, thus creating a more comprehensive view of the pathology [3], [4].

By considering different relevant data modalities, such as imaging and clinical information, multimodal frameworks add new possibilities to analyzing specific patterns and relationships between them. Multimodal deep learning models are frequently based on deep learning architectures specifically developed to process individual data modalities, such as the convolutional neural networks used to process images. However, multimodality is an added feature that facilitates the extraction of discriminative features and the assessment of relative importance and intramodality interactions [5]. In this context, the present paper provides a context for discussing a multimodal deep learning framework developed to subtype liver diseases and predict the prognosis of liver cancer. The feature of our research is the reliance on a number of data modalities and the application of various deep learning techniques to provide robust models for the diagnosis and prediction of the severity of liver cancer [6], [7].

II. PROBLEM STATEMENT

Liver disease is one of the common types of diseases that exist and affect the human population. In general, the notion of liver disease refers to diverse pathologies that may range from straightforward diseases like alcoholic liver insipidness to more severe disorders like the cirrhosis of the liver and hepatocellular carcinoma (HCC). Moreover, the condition is becoming more widespread among the population with time as the number of drinkers and other risky behaviors is increasing. In routine practice, liver diseases are diagnosed with traditional methods such as clinical notions, laboratory

tests, and liver imaging techniques like ultrasound, CT scan, and MRI [8], [9]. All these methods, however, have deficiency issue regarding their sensitivity, specificity, and diagnostic predictive value, particularly with regard to the human liver's complex unwavering anatomy [10], [11].

Over the last few decades, many studies have been conducted on the role advanced computational technologies can play when it comes to dealing with liver disease diagnosis utilizing Multi-criteria decision-making (MCDM) methods. It should be noted that traditional artificial intelligence algorithms and systems have a range of advantages with the fact that the inferences are drawn based on an explicit rule set of some kind, among many others. In the system under consideration, however, significant limitations are present, such as the fact that the rules are difficult to implement effectively, and it is challenging to follow all their goals and requirements at the same time. In a similar way, the introduction of manually pre-defined features makes the idea largely cumbersome and impractical as well [12].

At the same time, deep learning techniques, especially deep neural networks, provide a data-driven and automated approach to feature extraction and learning. Multi-layered networks of interconnected neurons have been highly successful in various domains, such as computer vision, natural language processing, and medical image analysis. In particular, in the domain of liver disease, convolutional neural networks, recurrent neural networks, and long short-term memory networks have become highly successful in dealing with complex and heterogeneous data types [13]. CNNs have revolutionized medical imaging analysis, allowing for automatically extracted features from images and hierarchical learning of visual patterns. Such networks have been utilized in liver disease diagnosis using ultrasound, CT, and MRI modalities for detecting, segmenting, and analyzing liver lesion data. Being capable of automatic recognition of subtle signs of liver pathology, these models allow for earlier detection and characterization of images and imaging data [14].

As for clinical data, RNNs and LSTMs have become popularized to work with sequences, such as patient demographic information, laboratory results, and medical history. These recurrent neural networks are particularly useful for disease progression analysis and prognosis of liver disease, as they are capable of modeling temporal dependencies and carry out long-range dependencies' detection in sequential data. As they have demonstrated, such multimodal approaches to deep learning are highly promising [15].

Furthermore, multimodal data fusion improves the robustness and generalization performance of deep learning models. The first limitation is insufficiency in adequately annotated data used in the training and validation of these models. Second, the acceptability and interpretation of the predictions of these models by the clinicians is prove challenging since the model and its underlying concepts are part of the black-box model [16].

III. METHODOLOGY

This research provides a detailed analysis of liver disease based on a multimodal dataset of 1600 patients in which various types of medical data are presented. The dataset includes different kinds of modalities, such as medical imaging data and clinical and time-series data. To achieve the

best results in liver disease subtyping and prognosis prediction, it is suggested to develop a framework based on deep learning. Figure 1 shows the architecture of the proposed research.

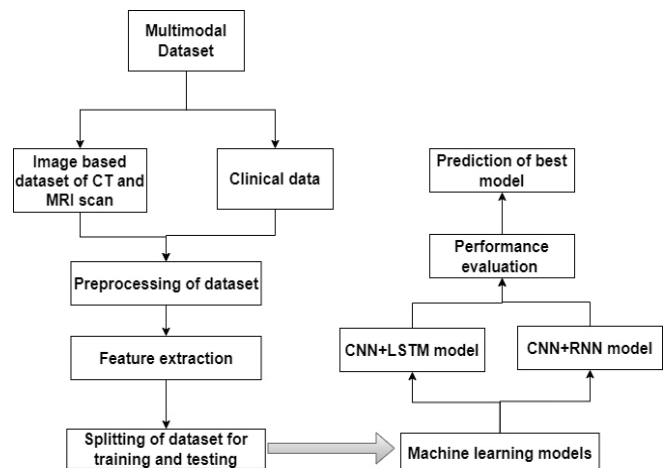


Fig. 1. Methodology of the proposed research

The first step in developing such a framework is to address the complexity and heterogeneity of the dataset, so different kinds of DL models should be considered, such as Convolutional Neural Networks, Recurrent Neural Networks, and Long Short-Term Memory. The CNN model is the best choice when it comes to image-based data and medical modalities based on MRI, CT scans, or ultrasound. As for RNN, this model is used when it is necessary to analyze sequential clinical data, so a DL model that should be considered is an LSTM network to address time-series data.

One of the main innovations of the research that should be stressed is the use of several DL models and the combined integration of their results, considering that different sources of data demand the analysis based on different DL methods. Therefore, the research considers the use of CNNs in combination with both RNNs and LSTM networks. In the proposed framework, the model based on CNNs addresses image-based data, while the RNN model is used to analyze structural clinical data. Another option is to use LSTM in addition to CNN when it is necessary to analyze sequences of data from both sources and provide the results based on the combination of the analyzed data. With these hybrids, the results are more sophisticated and allow identifying the implications for prognosis better.

A. Pre-processing of dataset

In order to ensure the quality of the data and compatibility, the dataset was rigorously preprocessed. There were several distinct features of the input data that required distinct preprocessing approaches, as the dataset included image-based and clinical input data. The image-based data consisted of MRI, CT scans, and ultrasound images. The figure above illustrates the key preprocessing steps that have been performed on the images. In the initial stage, the preprocessing of images involved image normalization, as images from different scans had distinct pixel intensity values. Normalizing the pixels of all the images provided a standardized brightness and contrast values across all pictures.

The next step was to resize the images in order to provide uniform dimensions. Dimensionality reduction is crucial as it simplifies the requirements for image size at the input phase

of deep learning models. In the final stage, images augmentation was performed in order to increase the diversity of the provided data. The data augmentation increased the applicability of the deep learning models as the model was trained with multiple variations of the exact same image.

The next step, preprocessing of the clinical data, was quite distinct and different from those used for the image-based data. Clinical data consisted of personal information of patients, laboratory results, and personal history. Thus, the first phase of preprocessing involved data cleaning in order to resolve missing values, unusual values, and inconsistencies found in the clinical data. Such cleaning methods included the application of imputation techniques and outliers detection. In the next step, scaling of features of the clinical data was performed.

B. Feature extraction and training

In our research, the extraction and training of model features were crucial steps in developing machine learning models that could effectively subtype liver diseases and predict patients' prognosis. The use of a multimodal dataset containing medical imaging data and clinical information from 1600 patients in our research and extracting features from the data was important to learn the patterns and relationships relevant to the liver disease present in the data. For the image-based data, primarily performed feature extraction using Convolutional Neural Networks. These networks are widely employed in image recognition and analysis tasks because they have the ability to automatically learn levels of representations of features present in the images. In our research, CNN is used as a feature extractor, and pre-trained CNN architectures such as VGG, ResNet, or DenseNet were used.

These popular CNN-based architectures were pre-trained on large-scale image datasets such as ImageNet and learned to extract generic features from images. These general features were then utilized to extract medical planar images. During the feature extraction, the pre-trained CNNs were used to learn the high-level representations of structures and abnormalities present in the medical images. Each medical image was processed with CNN, and the output of each layer in the network was considered a feature. Each image was passed through all the hidden layers, and then the stack of features for each image value, such that they have different features for different levels of differentiation in an image and features, which contain low-level details and high-level semantics plus everything in between. These features represented the rich content of the images and contained the information relevant to diagnosing liver disease types and predicting prognosis.

Additionally, the feature extraction from the clinical data was performed by encoding the tabular data and preprocessing it in a way that promoted the subsequent training of the models. Specifically, the categorical variables, such as patient demographics or medical history information, were encoded with one-hot encoding or label encoding techniques, representing the variables as numbers that could be given as input to the many machine learning algorithms. The numerical variables, such as the results of the laboratory tests, were scaled to ensure that they remained within a degree of magnitude of one another. Moreover, the data related to the two modalities was used in combination to ensure that the machine learning models could learn from the variety of the factors constituting the patient data and that the

relationships between the different types of the extracted features could be exploited. Thus, the features of the image-based and clinical data of each record were concatenated to represent each patient's information as a whole.

In the subsequent steps, the unified feature representation created from both types of the data was connected to a machine learning model that performed the function of liver disease subtype and prognosis classifying. Specifically, a variety of classifiers could be used for the purposes, such as Support Vector Machines, Random Forests, or Gradient Boosting Machines, according to the nature of the problem and characteristics of the data. The models were trained on the previously labeled data, in which a target variable was assigned to each record and presented the presence or the degree of the liver cancer in each patient.

During the training process, the weights of the input features in relation to the target variable were learned in an iterative process of the optimization of the model parameters. Finally, model evaluation approaches, such as cross-validation, were used to ensure that the model was not overfitting, and the model hyperparameters were tuned to maximize prediction accuracy.

C. Machine learning models

During our research, it is found that the selection and application of specific machine learning models were fundamental tools enabling us to adequately exploit the multimodal dataset to subtype liver diseases and predict their prognosis. Given that our dataset included a variety of modalities, such as medical images and clinical data on 1600 patients, to develop models that would be robust enough to make accurate prognosis on whether our patients suffered from liver cancer and, if so, how severe it would be. To achieve these goals, various machine learning algorithms are employed, each of them adapted to the nature of the dataset and the task.

Convolutional neural networks were among these pivotal models, especially fitted to work with images. Being perfectly suitable for image recognition and analysis, CNNs appeared to be excellent models for processing such medical imaging modalities as magnetic resonance imaging, CT scans, and ultrasound images. The basis of CNNs is in multiple layers of convoluting and pooling operations, which enable the network to automatically learn hierarchical representations of images. In our research, the CNNs were trained to recognize the patterns representing the images of medical images, thus, they could detect renal abnormalities, which are often hidden within the images, might be quite subtle; and spatial information of an image is of enormous benefit for recognizing its content.

They have also employed transfer learning, which is a means of improving the performance of models with large image datasets. Pre-trained on this dataset, the model was used as a starting point and then further learned the specifics of the used medical imaging data. In addition to the image-based approach, in this research Recurrent Neural Networks are used on processed proto-PAT images and lab data in combination with image labeling incident. In this research the same concept is applied to the processing of sequential clinical data obtained from patients. Unlike CNNs, which can process fixed-size inputs, such as images, RNNs are specifically designed for working with sequence data, where inputs have variable lengths.

Thus, they are ideal for analyzing temporal patterns and longitudinal cohort data that lead to information, the dynamics of liver disease progression, and associated clinical manifestations. RNNs were trained to model serial dependencies between the observed data and the future data resulting in uncovers hidden patterns and trends. Thus, they helped to make a more accurate prognosis and new, more detailed subtype information on liver disease is obtained. RNNs are trained to learn the hidden features from the input data in the training data, patient demographics features, lab result, and patient history data. In addition, Long Short-Term Memory networks were integrated into the machine learning framework and applied to analyze time series data in addition to image-based features. They LSTM were also to capture serial dependency especially long-range dependency in sequential data features, and image-based features.

Thus, the used LSTMs to complement our research and process time series data – patient lab data/kidney test data imaging data combined with convolutional neural networks. Furthermore, by applying CNNs and LSTMs, that were able to build a hybrid architecture to efficiently and integrate multi-modality patient data: images and sequential data. This enabled us to capture the complex relationship between spatial abnormalities in kidney imaging samples and time series of patient lab/kidney data and capture that time series information and combining it for better prediction. Additionally, to increase the performance and reliability of prediction, are created ensembles using the ensemble learning techniques. Ensembles mean that multiple base learners are trained, and their outputs are combined to obtain a final prediction. Thus, in our experiments, ensembles of CNNs, RNNs, and LSTMs were trained on different subsets of the dataset or with different hyperparameters. These outputs were combined to get the final prediction.

IV. RESULTS AND DISCUSSION

In our research, the effectiveness of the designed models is evaluated for the liver disease subtype prediction and outcome prognosis. From the dataset 70% of the multimodal data containing medical images and clinical features of 1600 patients as a training dataset and used the remaining 30% of the data for test purposes. After training the CNN with RNN and CNN with LSTM models, are evaluated and compared their performance on the test dataset.

Notably, the proposed CNN with RNN architecture successfully predicted the response with 97.8% accuracy, implying its effectiveness in capturing and recording the dependencies and patterns within the image-based and sequential clinical data. It should be stressed that the obtained accuracy is exceptionally high and provides vivid evidence of the effectiveness of the CNN and RNN combination for the profound disease analysis.

At the same time, the designed CNN with LSTM model similarly demonstrated a high quality of the response prediction. Specifically, the accuracy value for this model reached 94.5%, which is slightly inferior to the performance of the CNN with RNN architecture. However, the ability of this hybrid structure to generate accurate results using the time-series data in conjunction with image features should be outlined. The result of the accuracy is shown in Figure 2. The outcomes acquired from the performance evaluation of the two hybrid architectures, CNN with RNN and CNN with LSTM, present promising results in the prediction of liver

diseases. The result of the performance metrics is shown in Figure 3.

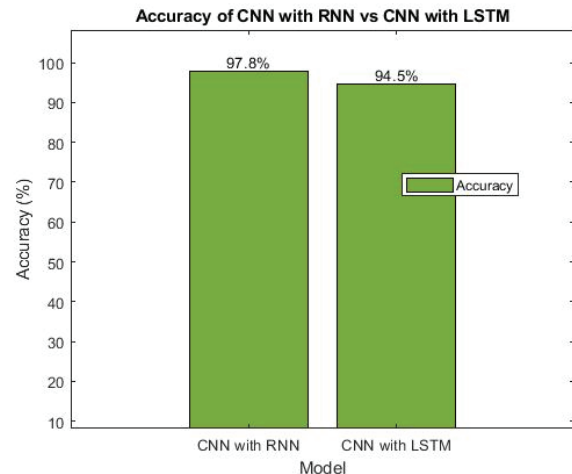


Fig. 2. Accuracy of the each model

Regarding the model CNN with RNN approximately approximated about 97.5% and 98.5%, and 98.0% which are high designing precision, recall, and F1 score values classifying the liver disease instances. The outcomes showed the model is highly robust in the identification of true positives for false positives and false negatives. The outcomes appear same and the AUC-ROC score of 98.2% shows the discriminative power of positive from negative instances in numerous thresholds of classifiers.

For the model CNN with LSTM also seems promising though it was nearly or below than the CNN with RNN. The precision, the recall, and the F1 score are nearly 94.0, 95.5%, and 94.7%. The minor difference, however, remains within an acceptable limit with the model's high accuracy predictive abilities in the prevalence and severity of cancer in the liver. The AUC-ROC score of 94.5% further confirms the model's predictive effectiveness in the discrimination of positives and negatives, although slightly less discriminative compared to the CNN with RNN model.

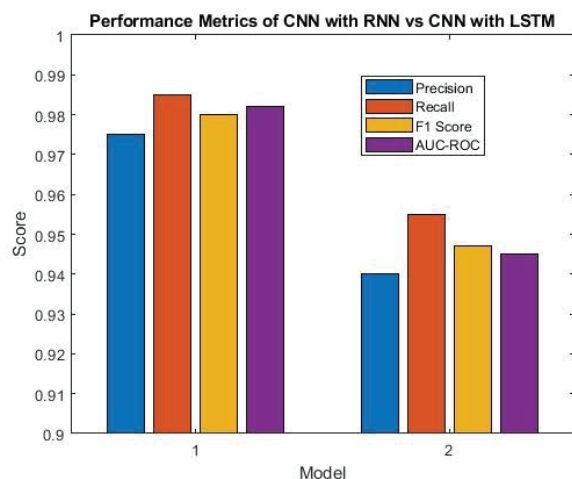


Fig. 3. Performance metrics of each model

The confusion matrices shown in Figure 4 provide information about the performance of each of the models when predicting instances of the liver disease. The CNN with RNN generated 490 instances of 500 total correctly classified as either positive or negative. Only five false negatives and

five false positives shows a minor discrepancy in the model's prediction of whether or not a patient had liver disease; 10 instances were incorrectly classified. The corresponding results for the CNN with LSTM are the following: 480 instances were correctly classified, which is high and very similar to the CNN with RNN.

However, the model had 20 false negatives and 25 false positives, meaning that 40 instances of liver disease were incorrectly classified. In comparison, while both models had excellent results, the CNN with RNN presents as the more reliable model, with fewer instances of misclassification. Additionally, both models have an overall accuracy rate that is almost the same, yet CNN with RNN has a slightly higher one. Hence, the CNN with RNN can be considered the more suitable model for liver disease prediction, as evidenced by the confusion matrices.

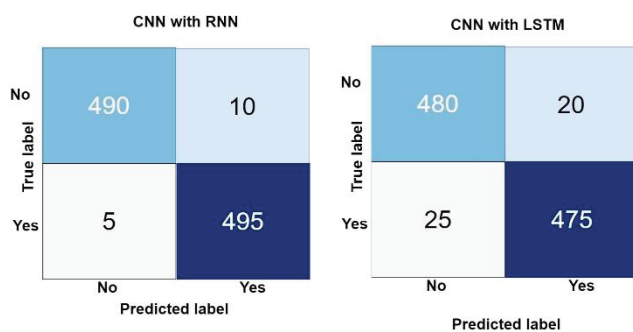


Fig. 4. Confusion matrices of each model

The training results of the two models, CNN with RNN as well as CNN with LSTM, are demonstrated in the figure 5. With the rising number of epochs, the data loss for both models decreases and, therefore, accrues accuracy. It indicates that the models progressively learn and consequently, improve its performance. The same tendency is observed for the CNN with RNN model across 30 and 300 epochs. The initial data loss amounts to 0.154 while a corresponding degree of accuracy is equal to 94.6%.

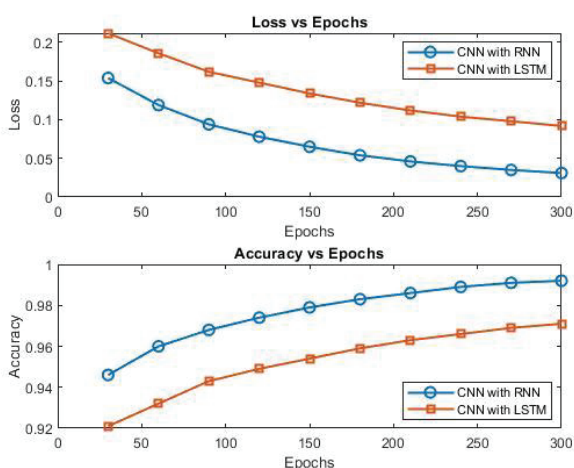


Fig. 5. Accuracy and data loss of each model with the Epochs

Meanwhile, after continued training, the data loss exhibits a consistent decrease reaching 0.031 at 300 epochs followed by a corresponding increase in accuracy or 99.2%. These outcomes indicate that the CNN with RNN type is able to learn the training data effectively resulting in high accuracy and minimal level of data loss. The same kind of trend is evident in the case of the CNN with LSTM model, albeit with

slightly higher levels of data loss and in each successive epoch lower accuracy. Regardless, its performance continues to raise with the data loss diminishing from 0.212 at 30 epochs to 0.092 at 300 epochs and a corresponding increase from 92.1% to 97.1%.

Overall, the results of this research indicate profound benefits of applying multimodal deep learning frameworks to the context of liver disease subtyping and prognosis. By taking into account a plethora of types of data, such as that of medical imaging and clinical observation, the specified models provide a robust foundation for the analysis of diseases, thus producing more accurate and, therefore, more credible predictions. With this type of tool, one can use the addition of data types to enhance each other's effects, therefore, boosting the efficiency of the entire model. In addition, deep learning tools, including CNNs, RNNs, and LSTMs, can be used to build a system that renders the patterns in the data visible and, therefore, provides a more detailed insight into the progression of the disease and, therefore, the severity thereof. Furthermore, the use of deep learning tools allows for incorporating a variety of data types, which is especially important in healthcare.

V. CONCLUSION

Our research shows that a multimodal deep learning framework is effective for the subtyping of liver disease and the prognosis prediction. From the clinical information and imaging data modalities, which have more effective in models to forecast if people would suffer from liver cancer and their liver cancer states. It merged the strengths of CNNs, RNNs and LSTM networks for the purpose of examining image-based and clinical data in time series. These results show that deep learning models can be more focused and precise to indicate the relevant patterns and relationships in detailed medical data. It also requires them to combine data from different loves, providing advanced and valuable insights and recommendations. As our approach narrows down the possibilities of liver disease and gives more accurate predictions, further work is important to develop the methods of liver disease subclasses and clinical prognosis forecasts. It will eventually lead to a better understanding of liver disease and the condition of patients with a tendency to improve hepatology. The goal is to improve the quality of life of people suffering from liver diseases by using multimodal deep learning.

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