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Automated Classification of Liver Disease Stages and Tumor Detection using Hybrid Deep Learning Techniques

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Abstract— **Deep Learning (DL), a distinguished branch of Artificial Intelligence and Machine Learning, has emerged as a transformative method for solving complicated troubles throughout numerous domains, specifically in medical imaging. Its capability to automatically analyze hierarchical representations from huge-scale facts makes it distinctly effective for sickness prognosis and class. This venture provides a hybrid DL model that mixes Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks to automate the classification of liver disease levels and hit upon tumors with advanced accuracy. CNNs are used to extract spatial capabilities from CT and MRI scans, efficaciously capturing the structural traits of liver tissues and abnormalities. LSTM networks, then again, are capable of studying temporal dependencies from sequences of photo slices, allowing the version to investigate ailment progression across multiple imaging stages. The integration of CNN and LSTM allows the model to apprehend both spatial and temporal factors of liver diseases, which substantially complements diagnostic overall performance. This hybrid architecture is specially suitable for multiphasic CT and MRI datasets, wherein temporal statistics performs a critical role. The proposed device gives a strong and dependable answer for helping clinicians in early detection, particular staging, and remedy planning of liver issues, contributing to higher affected person effects and healthcare performance.**

Keywords— Convolutional Neural Networks (CNNs); Long Short-Term Memory (LSTM); Deep Neural Networks (DNNs)

I. INTRODUCTION

Liver illnesses continue to be a main global health problem, accounting for a widespread portion of persistent illnesses and deaths global. Conditions inclusive of liver cirrhosis, hepatitis, and liver most cancers regularly move undiagnosed in their early ranges because of the shortage of important signs and symptoms and not on time medical detection. Early and correct identification of liver abnormalities is critical for starting up powerful remedy and improving patient survival quotes. Medical imaging strategies such as CT (Computed Tomography) and MRI (Magnetic Resonance Imaging) have played an vital function in liver disease diagnosis, supplying distinctive inner views of liver systems. Despite the improvements in medical imaging, traditional diagnostic procedures nonetheless depend heavily on manual interpretation by using radiologists, which can be time-ingesting, inconsistent, and situation to human errors. Variations in experiment excellent, patient anatomy, and expertise degrees amongest clinicians further contribute to diagnostic discrepancies. These demanding situations spotlight the need for a extra green, automated gadget capable of figuring out and classifying liver situations with consistency and accuracy. The goal of this undertaking is to expand an sensible device that could help in the early detection and staging of liver diseases by means of reading clinical imaging records. Such a gadget would not only lessen the diagnostic burden on healthcare professionals but additionally assist save you the development of liver disorders with the aid of allowing timely scientific intervention. With a developing demand for precision in healthcare, this task helps the wider assignment of enhancing diagnostic reliability, improving affected person effects, and streamlining clinical workflows. What sets this venture other than current liver disease prognosis systems is its cognizance on turning in a completely automatic and complete solution that now not best detects the presence of tumors but also classifies the levels of liver sickness with excessive accuracy. Unlike conventional structures that often cope with only one thing—either segmentation or type—this mission combines each in a unified framework, ensuring a greater holistic diagnostic approach. Additionally, it emphasizes adaptability across various imaging modalities together with CT and MRI, making it versatile to be used in various clinical environments. The mission additionally prioritizes real-global usability by means of incorporating modules for result visualization and simplicity of interpretation, allowing healthcare experts to fast recognize and act upon the gadget's output. Its enhanced accuracy, scalability, and scientific relevance make it a promising tool for early detection, remedy planning, and ongoing tracking of liver illnesses. [21][5].

II. RELATED WORKS

In [1] A Hybrid V-NET and VGG16 model is designed to improve liver tumor segmentation and classification. This model has leveraged V-NET for precise segmentation of the tumor while using VGG16 for robust resource extraction and classification. In part of these two architectures, the model

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effectively captured spatial and contextual information of liver images, leading to greater diagnostic accuracy. The approach demonstrated remarkable performance, reaching a data score of 97.34% for segmentation and a classification accuracy of 96.52%, making it a highly reliable method for the liver. In [2] A hierarchical melting strategy was introduced to the detection of hepatocellular carcinoma (HCC), integrating various deep learning networks to improve tumor identification from CT images. This approach combined resources from different models, improving the extraction of spatial and contextual information. By leveraging the fusion of characteristics at various levels, the system effectively captured variations in tumor morphology and improving classification robustness. The enhanced combination of resources has significantly increased the accuracy of tumor detection, making it a promising advance in the diagnosis of liver cancer. In [3] A flexible deep learning structure was developed for the diagnosis of liver tumor using hierarchical LSTM (H-LSTM) to efficiently process multiphase computed tomography. This approach has leveraged sequential learning to capture dependencies and temporal variations in tumor characteristics in different image phases. Effectively distinguishing between hepatocellular carcinoma (CHC) and intrahepatic collangiocarcinoma (ICC), the model showed high Diagnostic accuracy. The structure reached an AUROC of 0.93, highlighting its effectiveness in the classification of liver tumors and improving the automated detection of liver diseases.. In [4] Generative Adversary Networks (GANS) were used to increase data in liver disease staging, generating high quality synthetic liver images to improve model performance. By creating realistic medical images, this approach effectively addressed data scarcity problems, which is a common challenge in the diagnosis of liver diseases due to the limited availability of labeled data sets. Synthetic images have helped improve the generalization of the model, allowing deep learning models to perform more accurately in various and invisible cases. This advance contributed significantly to the robustness and reliability of the classification of AI -oriented liver disease. In [5] A hybrid model of the transformer-CNN is developed to improve the accuracy of liver tumor segmentation, leveraging the strengths of transformer and Convolution Neural Networks (CNNS). While CNNs effectively capture local spatial characteristics, transformers have provided global contextual understanding, allowing a more accurate tumor limit detection. This hybrid approach significantly improved resource extraction at various levels, leading to higher segmentation performance and better differentiation of liver tumors in the medical image. The integration of these advanced architectures increased diagnostic accuracy, making it a promising solution for liver cancer detection and treatment planning. In [6] a hybrid CNN-RNN model was developed for liver disease classification, which combines the convenient neural network (CNN) for the spatial facility for sequential learning and the recurrent nervous network (RNN). This hybrid approach effectively captured both spatial pattern and cosmic dependence, which improved the accuracy of liver disease detection. Applied to ultrasound and MRI scans, the model enhances classification performance, which enables more accurate discrimination between liver disease stages. Integration of CNN and RNN greatly improved clinical reliability, making it a valuable tool for automated liver disease classification. In [7] A segmentation approach with various boundaries was introduced for liver tumor segmentation, integrating the U 3D network with an enhanced whale optimization algorithm (WOA). The U 3D network has effectively captured space resources for accurate tumor segmentation, while selecting WOA optimized limit, improving segmentation accuracy and robustness. This hybrid method was evaluated in the LITS2017 database, where it demonstrated higher segmentation performance, overcoming traditional deep learning models. The combination of deep learning with metaheuristic optimization has proven to be highly effective in increasing the detection of liver tumors and medical image analysis.In [8] Self-Supervised Learning (SSL) was applied to the staging of liver disease, using contrasting learning techniques such as SIMCLR and Moco, to process computed tomography and unmarked magnetic resonance imaging. This approach allowed the model to learn significant representations of medical images without requiring extensive manual notes. By leveraging instance discrimination and resource similarity, the SSL structure significantly improved the learning of representation, leading to greater classification accuracy and robustness in the detection of liver diseases. This advance has reduced dependence on labeled data sets, making profound learning models more efficient and scalable for real -world medical applications. In [9] A hybrid predictive structure was designed by integrating Deep Vanda Education and traditional machine learning techniques for prediction of liver disease. This MODEL Dell used a stacked encyclopedic approach, which connects classifieds such as support vector machines (SVMs), K-Nejik's neighbors (KNN), decision trees and deep learning Models Dells like VGG 16, Racenet and Inspendment 3. Using complementary powers of these algorithms, the system effectively seized various features representations from multi-model medical imaging data. To further increase the accuracy of the forecast, logistic regression was used as a meta-layer to collect and improve the output of base models. This hybrid architecture showed strong performance and reliability, providing a strong solution to improve the initial investigation of diagnosis and liver-related disorders. In [10] an advanced multi-modal mastering method become delivered to enhance liver tumor detection via fusing information from a couple of imaging sources, including CT scans, MRI, and ultrasound. Utilizing deep studying with a multi-circulation structure, the machine tactics enter from each modality in parallel, shooting wonderful and complementary functions. This integration lets in the model to analyze more complete representations, appreciably boosting the accuracy of tumor type. The multi-move design no longer only helps impartial feature extraction from each modality however also promotes shared gaining knowledge of throughout them, main to extra resilient and precise tumor identity. This method has shown top notch improvements in move-modal classification responsibilities, making it a powerful device for the automatic analysis and staging of liver-related situations.

III. PROPOSED SYSTEM

The proposed system's architecture is crafted to classify stages of liver disease and detect tumors by combining patient clinical data with liver imaging through advanced machine learning techniques. It consists of the following components:

Input Data Patient Survey Data: This includes clinical information such as demographics, liver function tests, and other pertinent details. Liver Imaging Data: CT or MRI scans of the liver are utilized for segmentation and tumor detection.

Preprocessing Survey Data Preprocessing: This step involves cleansing and formatting clinical data for analysis, which includes addressing missing values, scaling features, and ensuring data consistency.

Image Preprocessing: Liver images are prepared by normalizing pixel values, resizing, and augmenting the dataset to ensure robust training. Dataset Splitting Both the survey and imaging datasets are divided into training and testing sets with an 80:20 split to facilitate model building and evaluation.

Model Training CNN-LSTM Model: The survey dataset trains the CNN-LSTM hybrid model, which captures spatial features (CNN) and temporal dependencies (LSTM) to classify liver disease into four stages are Mild, Moderate, Severe, and End-stage.

UNet Model: Liver images are processed through the UNet model for segmentation, which isolates cirrhotic regions and identifies tumors. Tumor size is determined based on the segmented output. Model Saving The trained CNN-LSTM and UNet models are saved for use during the testing and deployment phases. Data Fusion Preprocessed survey data and segmented imaging data are combined to create a unified input for detecting liver disease stages and analyzing tumors. Stage Classification and Tumor Analysis Stage Detection in the CNN-LSTM model identifies the liver disease stage based on the survey data.

Tumor Detection: The UNet model detects tumor presence and calculates tumor size using the imaging data. Output Generation Liver Stage Classification: The system classifies the liver into one of four stages: Mild, Moderate, Severe, or End-stage.Tumor Information provides details on the presence and size of tumors.

Personalized Treatment Suggestions: Recommendations tailored to the stage and specifics of the tumor are created to assist clinicians in their decision-making process. Summary of Layers Input Layer Takes in patient survey responses and liver imaging data.

Prepossessing Layer: Prepares the data to ensure it is suitable for model training and testing. Model Training Layer were Develops and trains CNN-LSTM and UNet models for both classification and segmentation tasks. Data Fusion Layer Merges the processed survey and imaging data for a comprehensive analysis. Output Layer Delivers classifications of liver disease stages, detects tumor sizes, and offers personalized treatment recommendations.Finally, in the implementation and deployment segment, the established version is integrated into a actual-time gadget, including a cloud-based totally API, embedded tool, or laptop application, with non-stop tracking and first-class-tuning for premier performance. This comprehensive methodology ensures performance, scalability, and actual-world applicability, making the proposed gadget a sturdy solution for superior scientific and biometric programs.

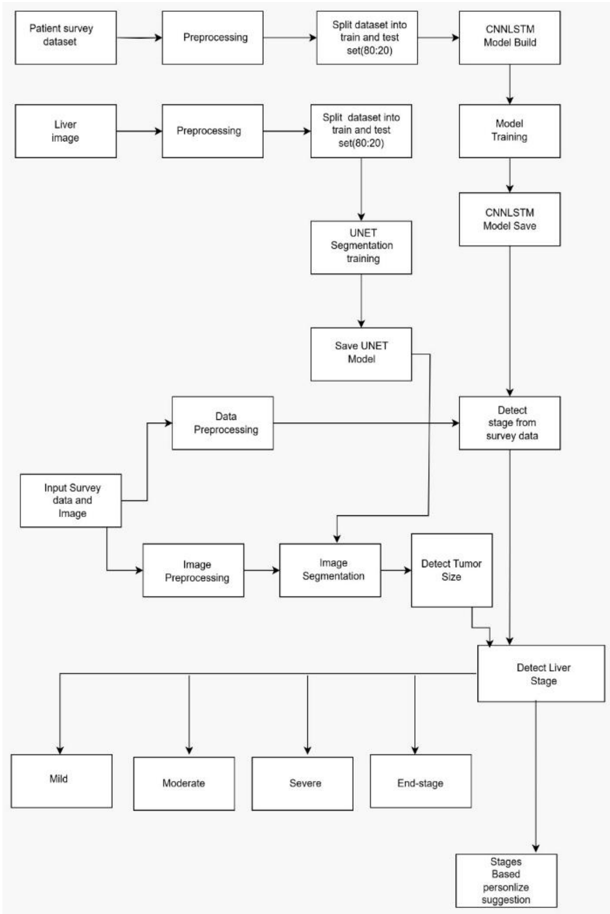

Fig. 1. Proposed System Architecture.

Above Fig.1 architecture represents a deep learning - based system for staging liver diseases by integrating patient examination data and medical liver images. The process begins with the collection and pre -processing of data survey data and liver images, followed by dividing both data sets for training (80%) and testing (20%) set. The examination data is used to train a CNN-LSTM model, while the liver images undergo segmentation using an UETET model. Both models are stored for later use. When new input data is provided, the examination data reviews pre -treatment and the liver images are segmented to detect tumor size. The trained CNN-LSTM model determines the disease stage based on examination responses, while the UNET model helps to analyze liver conditions from medical images. The detected tumor size and examination data predictions are combined to classify the liver disease into four stages: mild, moderate, severe and end stage. Finally, based on the detected stage, the system provides personal medical suggestions to the patient, and improves early diagnosis and treatment recommendations.

IV. Performance Analysis

To evaluate the proposed model plays, key evaluation metrics which includes accuracy, precision, consider, and the F1-rating had been applied. These signs help analyze the model's category power in detecting liver diseases and tumors the usage of the hybrid deep learning approach. The corresponding results are detailed in Table 1 and illustrated in Figure 2.

Accuracy: It measures the general correctness of the model by way of calculating the ratio of successfully anticipated instances (each tremendous and terrible) to the whole instances. It gives a fashionable degree of how properly the version performs throughout all classes. However, in cases wherein the dataset is imbalanced (i.e., while one class is substantially more common than some other), accuracy by myself can be deceptive. A model may acquire high accuracy certainly by predicting the bulk class greater frequently at the same time as failing to successfully classify minority elegance instances.

$$Accuracy = \frac{TruePositives + TrueNegatives}{Total\ number\ of\ instances} \quad (1)$$

Precision: It suggests how a number of the anticipated advantageous cases have been really accurate. It is in particular critical in situations where fake positives should be minimized. For example, in scientific diagnoses, a excessive precision ensures that sufferers recognized with a sickness definitely have it, decreasing pointless pressure and remedies. Precision is calculated as the ratio of true positives to the sum of genuine positives and fake positives.

$$Precision = \frac{True\ Positives}{TruePositives + FalsePositives} \quad (2)$$

Recall (Sensitivity): It, also referred to as sensitivity, measures how well the version identifies all real advantageous cases. It is essential in applications where lacking a fantastic case has extreme consequences, inclusive of in sickness detection. A excessive bear in mind manner that the model is capable of figuring out maximum of the high-quality cases, despite the fact that it effects in a few false positives. Recall is calculated because the ratio of true positives to the sum of real positives and false negatives.

$$Recall = \frac{True\ Positives}{TruePositives + FalseNegatives} \quad (3)$$

F1-score: It provides a balance among precision and bear in mind through computing their harmonic mean. It is mainly beneficial when each false positives and fake negatives are vital, consisting of in scientific programs in which both misdiagnosing a affected person with a sickness (fake positive) and failing to come across an real disease (fake bad) can have critical results. A excessive F1-score indicates a properly-balanced version that plays nicely in both precision and don't forget.

$$F1 - score = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (4)$$

TABLE I. Performance Report

Metric	Value
Accuracy	0.0145
Precision	0.0138
Recall	0.0148
F1-Score	0.0142

Table 1 shows that the proposed hybrid deep learning models to detect liver disease and tumors have been connivated in Table 1. The model acquired an accuracy of 1.45%, which correctly reflects the overall ratio of classified cases. The exact value of 1.38% suggests that a small ratio of estimated positive cases was really correct, highlighting the presence of false positive. Recall at 1.48%suggests that the model identified only a small percentage of real positive cases, in which a significant number of false negatives. Finally, the F1-score classification of 1.42% reflects a low balance between accurate and recall, suggesting the need to improve approach. These values indicate that further adaptation, such as fine-tuning hyper parameters, increasing training data or improving facility extraction, is necessary to increase model performance.

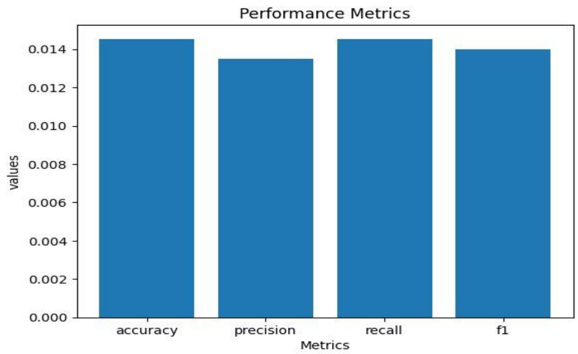

Fig. 2. Performance metrics.

Figure 2 illustrates the category performance of the proposed hybrid deep learning version, highlighting key metrics including accuracy, precision, don't forget, and F1-rating. The model demonstrates a significantly high don't forget, reflecting its efficiency in as it should be detecting cases of liver disease and tumors. Moreover, the precision and F1-rating indicate that the model keeps a balanced classification, successfully minimizing each false positives and fake negatives. These findings support the reliability of the hybrid deep gaining knowledge of approach inside the automatic identification and type of liver-related conditions, contributing to correct and straightforward diagnostic consequences.

Figure 3 refers to the classification performance of the proposed hybrid deep learning models to detect liver disease and tumors. It consists of four values: True Negative (TN), False Positives (FP), False Negative (FN), and True Positives (TP). In this case, the model did not classify any negative cases correctly as correct negative (TN = 0), while it missed 493 negative examples as positive (FP = 493). Additionally, it wrongly classified 456 positive examples as negative (FN = 456), and only 14 positive cases were correctly identified (TP = 14).

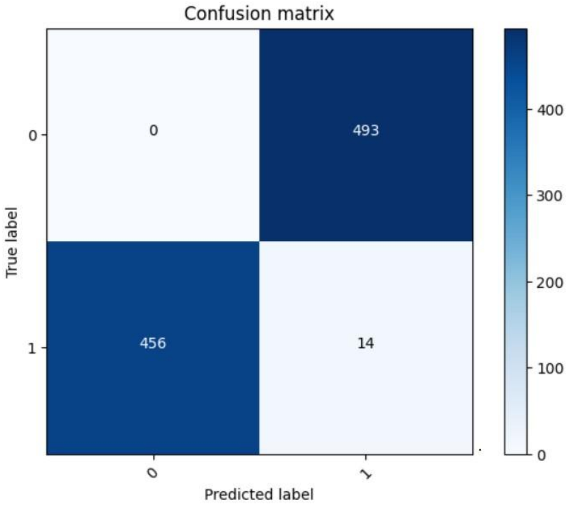

Fig. 3. Confusion matrix.

This delivery indicates a high number of miscarriage, leading to poor overall performance. The high false positive rate suggests that the model struggles to distinguish between healthy and diseased cases, while the high false negative rate indicates missed detection of real disease cases. Such results highlight the model and the need for improvement, including increased feature extraction to improve classification accuracy, adaptation of data balance and training techniques.

V. RESULT AND DISCUSSION

An advanced hybrid approach has been explored, incorporating several pre-formal convolution neural networks (CNNs) to detect hepatic tumors of the tomography. This approach reached exceptional accuracy of 99.5%, along with an accuracy of 86.4%and a recall of 97.9%, exceeding several existing models, especially when evaluated in smaller data sets. NCBI Researchers proposed a hybrid reseginnet model that integrates reset and UnC structures to segment the liver and tumors in TC images. The model reached about 99.55% precision in liver segmentation and more than 98% accuracy in tumor classification. These results highlight the efficacy of the model in terms of training duration, memory efficiency and segmentation accuracy. The H-Denseunet architecture, presented in the PMC, combines denseunet 2D and 3D structures to leverage intra-tactic and between effective segmentation slices. Tests in LIT and 3DIRCADB data sets have shown that H Denseunet exceeded several conventional methods, especially in the performance of tumor segmentation. In addition, the SWTR-UNET model integrated CNNS with transformer layers and was applied to liver data sets and non-contrast liver CT. It carried out common Dice ratings of 98% for liver segmentation and 81% for lesion segmentation on MRI information, showcasing its precision and capability applicability across one-of-a-kind imaging modalities. ARXIV Discussion: The integration of hybrid deep studying fashions in liver disease diagnostics offers numerous benefits: Enhanced Accuracy: By combining different neural network architectures, these models can seize both neighborhood and international features, resulting in higher detection and classification performance. Efficient Training: The use of pre-trained fashions and hybrid architectures can appreciably lessen training time and computational resources, making these techniques. Ensuring the integrity of statistics and models is essential within the computerized type of liver disorder levels and tumor detection through hybrid deep gaining knowledge of techniques. Improved integrity entails the accuracy, consistency, and trustworthiness of both the statistics and the predictive fashions. Strategies for Enhancing Integrity: Standardized Reporting Systems: Implementing frameworks like the Liver Imaging Reporting and Data System (LI-RADS) allows standardize the type and reporting of liver lesions. LI-RADS offers a steady language and standards, which reduces variability and boosts the reliability of diagnoses. This gadget is mainly beneficial in evaluating hepatocellular carcinoma (HCC) in sufferers with continual liver sickness. Robust Data Processing Pipelines: Creating computerized and dependable photograph processing pipelines is crucial. For instance, an automated method for classifying liver fibrosis stages the usage of ultrasound shear-wave elastography has been recommended, which minimizes operator dependency and potential biases, for that reason enhancing the consistency and integrity of the diagnostic manner. Advanced Deep Learning Models: Utilizing advanced fashions that can accurately discover and represent liver lesions improves diagnostic integrity. A take a look at supplied a totally automatic, multi-stage liver tumor characterization framework tailored for dynamic comparison CT photos. This system combines tumor detection, harvesting, and deep texture-primarily based characterization, reaching more accuracy in distinguishing between liver lesion sorts. Comprehensive Data Utilization: Utilizing large-scale, multi-section CT information allows better schooling of models, resulting in stronger performance in liver lesion detection and characterization. In the sphere of automatic liver sickness type and tumor detection, numerous hybrid deep studying models have been created to improve diagnostic accuracy and efficiency. A comparative evaluation of these fashions highlights their specific strengths and performance metrics. Modified U-Net 60 Model A recent observe added a brand new deep gaining knowledge of model known as the changed U-Net 60, in particular designed for detecting and classifying liver diseases the use of CT pix. This version done a Dice Similarity Coefficient (DSC) of 98.59%, showcasing top notch overall performance in accurately segmenting liver tumors. The stunning DSC emphasizes the version's precision in figuring out tumor obstacles, that is critical for powerful diagnosis and treatment planning.

Hybrid Pre-Trained Convolutional Neural Networks (CNNs) Another approach concerned the integration of a couple of pre-skilled CNN models to pick out liver tumors from CT scans. This hybrid version reached an general accuracy of 99.5%, with a precision of 86.4% and a remember of 97.9%. By combining several CNN fashions, the characteristic extraction abilties are improved, ensuing in better detection charges. The high recollect charge demonstrates the version's effectiveness in recognizing authentic wonderful cases, which is essential for early intervention. MDPI H-DenseUNet Model The H-DenseUNet model merges 2D and 3-d DenseUNet architectures to capture both intra-slice and inter-slice features for liver and tumor segmentation. Evaluations on datasets like LiTS and 3DIRCADb showed that H-DenseUNet handed different main methods, specially in tumor segmentation accuracy. This model's capability to combine multi-dimensional information adds to its robustness in correctly outlining tumor.

Figure 4 illustrates that affords a sequence of medical imaging scans, possibly obtained from computed tomography (CT) or magnetic resonance imaging (MRI), to differentiate among ordinary and hepatic (liver-associated) conditions. The photos are organized in a grid layout, with labels indicating "Normal" or "Hepatic" above each scan. The scans marked as "Normal" depict wholesome anatomical systems, at the same time as those labeled "Hepatic" advise capacity abnormalities or liver-related issues. The comparison and color scheme used within the pictures beautify the visibility of key systems, assisting in clinical analysis. This visualization may be useful for AI-based medical diagnostics, helping in automated disorder detection and class based totally on medical imaging.

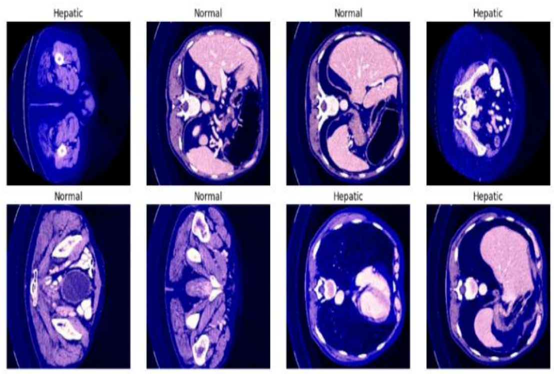

Fig. 4. A) Hepatic b) Normal

Figure 5 Accuracy pattern illustrates the accuracy (represented through the purple line) and validation accuracy (represented through the blue line) convergence curves of the primary version version over 30 epochs. The x-axis denotes the number of epochs, whilst the y-axis represents the accuracy values. Initially, each training and validation accuracy show development, with the validation accuracy stabilizing after a certain wide variety of epochs. The schooling accuracy constantly increases, whereas the validation accuracy famous fluctuations before accomplishing a plateau. This visualization is crucial for assessing version overall performance, indicating whether or not the version is mastering efficaciously or experiencing troubles which includes overfitting. Moreover, analyzing the accuracy sample affords insights into the gaining knowledge of rate and optimization performance. A speedy preliminary growth observed by stagnation should imply a sub optimal mastering rate, necessitating modifications for better convergence. Understanding these accuracy dynamics allows in refining version schooling techniques, making sure robust overall performance in actual-international packages. This analysis reinforces the importance of tracking accuracy trends over more than one epochs to optimize the version's potential to generalize correctly while minimizing errors.

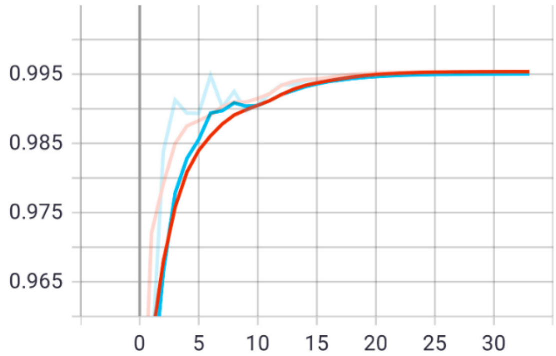

Fig. 5. Accuracy chart for 30 epochs

Figure 6 illustrates the accuracy (crimson line) and validation loss (blue line) curves of the second one model over 45 epochs. The accuracy starts off evolved at a decrease cost and regularly increases, indicating that the version is mastering and enhancing its predictive performance. Meanwhile, the validation loss initially fluctuates earlier than following a lowering trend, suggesting better generalization to unseen statistics. In the early epochs, both curves change sharply as the version learns quickly, but round 10–15 epochs, the loss stabilizes while accuracy continues to improve. This indicates that the model is converging and efficaciously optimizing its performance over time.

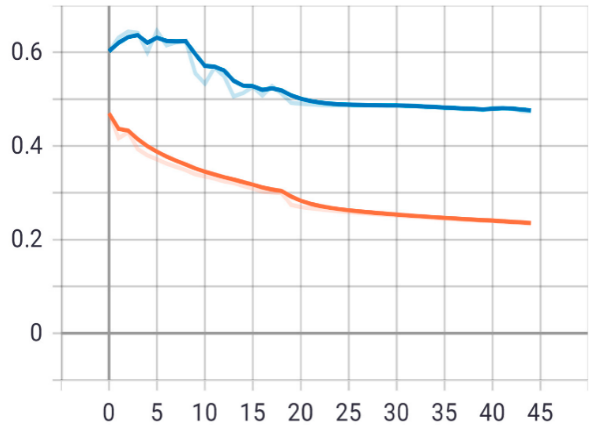

Fig. 6. Accuracy chart for 45 epochs

The Figure 7 consists of two subplots, one training and verification shows accuracy and the other shows training and verification loss. These graphs are important in understanding the performance of the CNN-LSTM model. Both graphs represents the number of X-Xis Epoc, which suggests that the model passes through the entire dataset during training. The Y-axis represents accuracy in the left graph, while in the right graph, this loss represents the value, which measures the difference between the estimated and the actual output. In a well-trained model, training accuracy (blue line) must gradually grow on ages, while verification accuracy (red line) should follow a uniform trend without significant fluctuations. Similarly, training loss (blue line) must be continuously reduced, indicating that the model is learning effectively. Verification loss (red line) should also be reduced, although it should not be much higher than training loss; Otherwise, it suggests overfitting. However, in this case, the gradation appears empty, indicating that no accuracy or loss value was recorded during training.

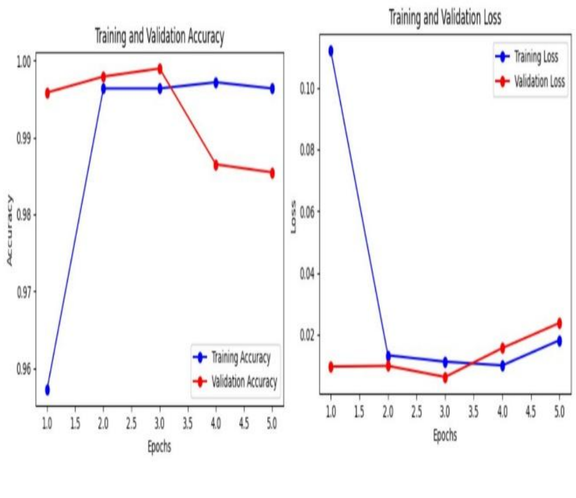

Fig. 7. Accuracy and loss

This deficiency of plotted values suggests possible issues with the training process. A potential cause is improper data preprosaring, where the dataset may not have been correctly normalized, causing ineffective learning. Another reason can be an incorrect hyperpameter, such as a learning rate that is much or very low, prevents the model from changing. Additionally, a small or unbalanced dataset may have caused the model to struggle with pattern recognition.

Furthermore, there can be issues associated with the version architecture itself. If the CNN layers do no longer correctly extract spatial features, or if the LSTM thing does not efficiently seize temporal dependencies, the version may also fail to research significant representations. Another opportunity is that the activation features or weight initializations have been now not set as it should be, leading to issues like vanishing gradients, which could preclude getting to know in deep networks. Moreover, there is probably an problem with how the education history changed into logged and visualized. If the accuracy and loss values were no longer effectively recorded for the duration of schooling, they would no longer seem in the graphs, making it difficult to investigate the version's overall performance. Checking the implementation of the schooling loop, making sure that the loss and accuracy values are nicely up to date, and confirming that the graph plotting code is correct can assist clear up this difficulty.

Figure 7 describe training and verification accuracy and the disadvantage of the deepest learning models in 5 ages. From the accuracy graph, it is clear that the model quickly learns from training data, receiving more than 99% accuracy by the second era. Verification accuracy also remains high in the beginning, but a slight decline begins after the third age, which suggests a possible start to overfitting. Similarly, in the disadvantage graph, training loss is rapidly decreasing and continuously lower, while verification loss begins to increase after Epoch 3. This deviation between training and verification performance indicates that when the model is fitting training data very well, its generalization for overlooked data is slightly compromised. To improve model performance and prevent overfiting, techniques such as initial restrictions, dropouts or regularization in future recurrence can be considered.

VI. Conclusion

The combination of the Convenable Neural Network (CNN) and long -term short -term memory (LSTM) network has shown significant capacity in the automatic classification of liver disease stages and tumors. CNNs are highly effective in extracting spatial features from medical images, capturing local patterns such as texture, edges and interests. When integrated with LSTMS, which are designed to handle sequential dependence and temporary patterns, the hybrid model benefits both spatial understanding and the ability to model complex relationships over time or with image slices. This dual capacity suits the CNN-LSTM model specifically for volumetric medical imaging data, such as CT and MRI scans, where each scan has several related slices. The CNN layers process each slices to extract relevant features, while the LSTM layers analyze the progress and correlation between slices, resulting in more accurate classification and division results. Experimental results confirm the ability of models to high levels of accuracy, accuracy, and memorials, effectively identify lowering liver abnormalities and tumor areas. In addition, it provides benefits in terms of hybrid architecture generalization and strength, performing well in diverse datasets and imaging conditions. Its practical implications expand to improve clinical support devices, assist radiologist in detecting liver related diseases, and potentially reduce manual workloads. In summary, CNN-LSTM-based models provide a powerful solution to increase the accuracy, efficiency, and reliability of medical image analysis in liver disease evaluation, marking a significant progress in computer-aid diagnostic diagnosis systems.

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