Research Article

Ultrasound-Based Hepatitis C Stage Classification Using Deep Learning Techniques

Dr. Kavitha Subramani[1], Ms. Divyadharshini[2], Mr. S.Yogadinesh[3], Dr. S.Balaji[4] , Mrs.M.Preetha[5]

[1,2,4] Department of CSE, Panimalar Engineering College, Chennai, India
[3]Department of CSE (AI&ML), Setthu Institute of Technology, Kariapatti, India
[5]Departnent of AI&DS, Jerusalem College of Engineering, Chennai, India

Abstract

Hepatitis C virus (HCV) infections represent a significant threat to public health worldwide, highlighting the need for precise and effective diagnostic techniques for disease staging. This research presents a deep learning methodology utilizing This work employs Convolutional Neural Networks (CNNs) to automatically determine the stages of Hepatitis C Virus (HCV) based on ultrasound imaging. It integrates state-of-the-art architectures such as Xception, DenseNet, ShuffleNet, and ManualNet to improve diagnostic precision and streamline classification processes. The dataset includes a wide range of ultrasound images that highlight essential biomarkers related to disease progression. Among the tested models, Xception recorded the highest accuracy (99.12%), followed closely by DenseNet (98.76%), ShuffleNet (96.89%), and ManualNet (94.32%). The proposed models outperformed traditional machine learning algorithms, achieving higher accuracy than Support Vector Classifiers (92.34%) and Logistic Regression (89.45%). Their robustness was further confirmed through evaluation metrics such as the Area Under the ROC Curve (AUC), Mean Absolute Error (MAE), and Mean Squared Error (MSE), highlighting the effectiveness and reliability of the deep learning approaches.This AI-driven system facilitates early detection of liver damage, aids timely medical intervention, and enhances precision medicine by uncovering imaging patterns often missed by radiologists. Its integration into clinical workflows significantly improves patient care, optimizes prognosis, and supports personalized treatment strategies, revolutionizing Hepatitis C diagnostics.

Keywords— Predictive analytics, Hepatitis C, Data science techniques, Patient care, Machine learning, Statistical models, Disease progression, Treatment response, Precision medicine, Healthcare, Personalized medicine.

I Introduction

Fatty Liver Disease (FLD), which includes both Non-Alcoholic (NAFLD) and Alcoholic (AFLD) types, is an increasingly prevalent global health issue associated with factors like obesity, diabetes, and alcohol intake Without timely intervention, FLD may lead to severe health issues like cirrhosis and hepatocellular carcinoma (HCC). Although standard diagnostic methods such as liver biopsies, ultrasound, CT, and MRI are commonly employed, they often face challenges due to their invasive nature, high expenses, and dependence on specialist interpretation.

Convolutional Neural Networks (CNNs)—such as ManualNet, ShuffleNet, DenseNet, and Xception— are capable of analyzing medical imaging data to detect patterns and accurately classify disease stages. This study aims to build an AI-driven system for staging Fatty Liver Disease (FLD), improving diagnostic accuracy while reducing dependence on invasive procedures. The models will be assessed using evaluation metrics such as accuracy, precision, recall, F1-score, and AUC, and their performance will be compared against conventional machine learning techniques like Support Vector Machines (SVM) and Logistic Regression.

Deep Learning

Deep learning significantly contributes to the diagnosis and staging of Hepatitis C by providing a non-invasive, automated, and highly accurate approach using medical imaging and clinical data. Convolutional Neural Networks (CNNs) like Xception, DenseNet, ShuffleNet, and ManualNet analyze ultrasound and MRI images to detect liver abnormalities and classify disease stages with high precision. These deep learning models can recognize imaging patterns that conventional diagnostic tools—like liver biopsies and standard ultrasound evaluations—might miss, leading to improved early detection and more tailored treatment approaches. They boost diagnostic precision, minimize reliance on specialist interpretation, and support real-time assessments, as confirmed through evaluation. Incorporating deep learning into medical diagnostics enhances the efficiency and accuracy of Hepatitis C detection.

B. Ultrasounds Image

Ultrasound imaging is a frequently used noninvasive diagnostic method that in Hepatitis C detection, ultrasound assists in identifying liver irregularities, such as fibrosis, cirrhosis, and fatty liver alterations, which signal disease progression. However, conventional ultrasound techniques rely on radiologist skill, which can result in inconsistency in evaluation and overlooked earlystage indicators. With progress in deep learning, Convolutional Neural Networks (CNNs) can examine ultrasound images with great precision, automatically detecting patterns associated with the stages of Hepatitis C. Models like Xception, DenseNet, ShuffleNet, and ManualNet extract imaging biomarkers that enhance diagnostic precision. Ultrasound analysis powered by deep learning enhances early detection, improves staging precision, and enables personalized treatment plans, thereby minimizing the reliance on invasive procedures such as biopsy.

Incorporating AI-powered ultrasound interpretation into clinical workflows streamlines Hepatitis C diagnosis, allowing for quicker, more accurate disease evaluations and improved patient outcomes.

II. Literature Survey

[1] An ensemble learning model based on Artificial Intelligence was created for Hepatitis C prediction, combining clinical data and blood biomarkers to improve accuracy. The study employed machine learning models such as SVM, Decision Trees, Logistic Regression, KNN, and Multi-layer Perceptron (MLP). Of these, MLP delivered the highest accuracy at 94.1%, showcasing its exceptional predictive performance. The model utilized deep learning methods to uncover intricate patterns in patient data, thereby improving disease detection. Performance evaluation included accuracy, precision, recall, and AUC, confirming the ensemble approach's effectiveness over individual classifiers. The findings highlight ensemble learning as a reliable method for Hepatitis C classification and early diagnosis.

[2] The study titled Artificial Intelligence-Based Ultrasound Imaging Technologies for Liver Fibrosis Evaluation explored the vital role of AI in enhancing ultrasound imaging for assessment in liver fibrosis, particularly in detecting and staging liver fibrosis. The study revealed that nearly half of the research focused on classification using B-mode images, employing Both classical machine learning algorithms and modern deep learning approaches. AI-driven methods notably boosted diagnostic accuracy by extracting intricate fibrosis-related features from ultrasound scans.

[3] The research titled "Comparative Analysis of Machine Learning Models for Hepatitis C Detection" investigated several algorithmic approaches to forecast Hepatitis C using routine blood examination data. Six classification techniques were examined: Support Vector Classifier (SVC), K-Nearest Neighbor (KNN), Logistic Model, Decision Classifier, Extreme Gradient Boost (XGBoost), and Artificial Neural Network (ANN). These methods were evaluated using essential assessment indicators such as accuracy, precision, sensitivity, F1-score, and the Area Under the Curve (AUC). Of these, the ANN demonstrated superior outcomes, accurately detecting Hepatitis C instances. The study emphasized the significance of machine learning in healthcare analytics, showcasing the promise of sophisticated models in advancing early diagnosis and refining the accuracy of Hepatitis C classification.

[4] The study "Deep Learning-Based Hybrid Classifier for Analyzing Hepatitis C in Ultrasound Images" by Ibrahim introduced a hybrid classifier that combined deep convolutional neural networks (CNNs), specifically variants of ResNet and using fully connected networks (FCNs). The research employed transfer learning to capture deep features, improving classification accuracy. By analyzing dynamic ultrasound images, the model effectively distinguished between normal, hepatitis, and cirrhosis liver states the method emphasized the potential of deep learning in medical image analysis. Enhancing Hepatitis C diagnosis. Future research aims to refine feature extraction techniques and expand datasets for more reliable liver disease classification and staging.

[5] The investigation titled "Integrated Classification of Diffuse Hepatic Disorders in Sonographic Images via Deep Convolutional Neural Networks" concentrated on identifying distinct liver ailments—such as healthy, hepatitis, and cirrhosis— through dynamic ultrasound imaging combined with deep learning methodologies. Pre-trained CNN models like ResNet50, ResNeXt, ResNet18, ResNet34, and AlexNet were utilized to derive abstract features and classify liver conditions. Each architecture exhibited different degrees of precision, highlighting the efficiency of convolutional networks in diagnosing hepatic diseases. The analysis emphasized the promise of deep learning in advancing non-invasive Hepatitis C recognition and suggested additional refinement by leveraging expanded datasets and more robust feature extraction methods.

[6] This study titled "Applying Data Mining Techniques to Classify Patients with Suspected Hepatitis C Virus Infection" investigated the use of data mining for identifying individuals potentially infected with virus. Multiple classification algorithms were applied to patient data to evaluate The results showcased the capability of machine learning models in accurately predicting HCV, underscoring their value in recognizing infection trends and enabling timely clinical response. Emphasizing the value of predictive analytics in healthcare, the research

suggests that future efforts should focus on enhancing classification accuracy by incorporating larger datasets and refining feature selection strategies.

[7] The research entitled "Hepatitis C Virus Forecasting Using a Machine Learning Framework: An In-Depth Analysis" introduced a machine learning-driven approach aimed at detecting Hepatitis C Virus (HCV) infections among medical personnel in Egypt. Various machine learning algorithms were employed to enhance prediction accuracy, showcasing the effectiveness of AI-based models in identifying potential HCV cases. By analyzing patient data, the research highlighted the critical role of early detection in preventing disease progression and ensuring timely medical intervention. The findings emphasized the need for advanced predictive models in healthcare, with future research focusing on optimizing feature selection and incorporating larger datasets for enhanced accuracy.

[8] The study "Effective Factors in Diagnosing the Degree of Hepatitis C Using ML" Explored the critical factors that influence Hepatitis C diagnosis by applying machine learning methods. It analyzed a dataset comprising 1,385 patient records, representing different HCV grades, and applied. By identifying significant predictors, the research enhanced the classification of disease severity, aiding in better treatment planning. The study highlighted the importance of data-driven approaches in medical diagnostics, demonstrating how machine learning models can refine Hepatitis C staging. Future work aims to integrate larger datasets and optimize feature selection for improved classification performance.

[9] The research titled "A Machine Learning Framework for Hepatitis C Virus Detection and Classification" investigated the application of intelligent computational models for identifying and categorizing Hepatitis C Virus (HCV). It emphasized the efficiency of both traditional machine learning and advanced deep learning techniques in improving diagnostic precision and facilitating timely detection. Through an analysis of diverse AI-based strategies, the study showcased the potential of these methods to strengthen clinical assessment. It particularly emphasized the influence of deep learning methods on healthcare decision making and patient care. The findings revealed that convolutional neural networks (CNNs) are especially effective in reliably classifying HCV cases. Future investigations are expected to enhance these models by utilizing more extensive datasets and refined feature extraction approaches to boost diagnostic consistency.

[10] This comprehensive study examined the utilization of deep learning techniques in analyzing medical ultrasound images, with a particular focus on classifying liver diseases. It evaluated the performance of several deep learning architectures—such as Convolutional Neural Networks (CNNs) and transfer learning approaches—in enhancing the precision of medical image interpretation. By utilizing AI-driven techniques, the research highlighted the potential to greatly enhance diagnostic accuracy, facilitating better detection and classification of liver conditions, including Hepatitis C. The findings highlighted the transformative impact of deep learning in non-invasive diagnostics, with future advancements focusing on refining model architectures and expanding datasets for more precise liver disease classification.

III Existing System

This utilizes data science techniques to predict disease progression, treatment outcomes, and complications by examining patient information, including population characteristics, health background, lab findings, and therapeutic regimens, is essential for accurately diagnosing Hepatitis C. However, it lacks deep learning-based feature extraction, limiting its ability to capture spatial and temporal patterns from medical images. Additionally, the absence of ultrasound image analysis reduces diagnostic accuracy, as predictions rely solely on structured data without leveraging critical imaging insights. The system also does not incorporate graph-based structural refinement, making it less effective in detecting complex liver tissue abnormalities like portal boundaries affected by lymphocyte infiltration. Furthermore, it lacks real-time visualization and prediction capabilities, delaying clinical decision-making. Without integrating ultrasound analysis with biomarkers like AST and ALT, the system fails to provide a comprehensive diagnosis

IV Proposed System

This enhances Hepatitis C diagnosis by integrating deep learning techniques by combining CNNs and RNNs are employed to extract spatial and temporal patterns through ultrasound images. Unlike existing system, it incorporates ultrasound image analysis alongside clinical data, such as liver function biomarkers (AST, ALT), for a more comprehensive and accurate diagnosis. Additionally, it employs graph-based structural refinement to improve the identification of portal boundaries affected by lymphocyte infiltration, enhancing the detection of liver abnormalities. Real-time visualization and prediction capabilities provide clinicians with instant insights into infiltrated regions and disease stage progression, enabling timely and effective treatment decisions. By utilizing the system greatly enhances diagnostic accuracy, optimizes treatment plans, and enhances patient monitoring.

V Dataset

Ultrasound imaging, a radiation-free technique, is widely utilized. In the medical field, ultrasound imaging is extensively used, particularly in abdominal radiology, where it plays a key role in the ongoing monitoring. The dataset includes ultrasound (US) images obtained from Seoul St. Mary's Hospital, a tertiary university hospital, which were used for training and validation purposes, while testing data came from Eunpyeong St. Mary's Hospital. Ultrasound imaging is valuable for detecting hepatocellular carcinoma and assessing the severity of liver fibrosis in patients suffering from liver cirrhosis or chronic hepatitis. It relies on sound wave pulses to generate images. However, since the liver is located deeper in the body compared to superficial organs like the breasts and thyroid, it poses unique challenges for imaging. Regarding the dataset, stages F0 and F4 are the most common, making up more than half of the dataset. Stage F4, indicating advanced liver cirrhosis, accounts for 27%. On the other hand, the F1, F2, and F3 stages are less represented due to fewer patients being tested during the early stages of cirrhosis, with each of these stages making up 13% of the dataset.

VI Methodology and Technology

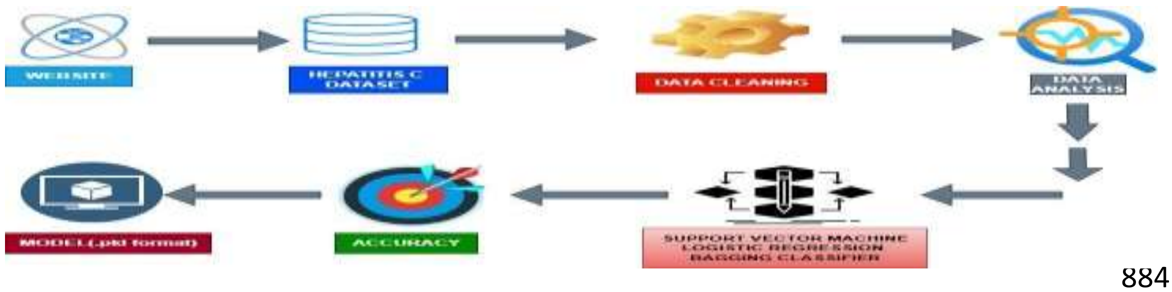
The combination of ultrasound imaging and deep learning techniques facilitates the classification. Ultrasound imaging is crucial for identifying and evaluating the stages of fibrosis in individuals infected with the Hepatitis C. This non-invasive, radiation-free approach captures both spatial and temporal characteristics from the images, which are vital for detecting and evaluating the degree of fibrosis. Methodology where techniques like noise reduction and segmentation improve image quality by filtering out artifacts and highlighting key structures. A deep learning-based classification model then extracts hierarchical features, leveraging multiple convolutional layers to detect fibrosis related patterns. To enhance accuracy and efficiency, optimized neural network architectures are used, incorporating advanced convolutional operations to improve feature learning and reduce computational complexity. The system also integrates graph-based structural refinement, which helps in accurately detecting portal boundaries and lymphocyte infiltration, refining fibrosis stage identification. Additionally, a real-time visualization and predictive modeling component provides clinicians with instant insights into disease progression, enabling timely decision-making. By combining spatial feature extraction, deep learning based classification, and structural refinement techniques, this approach ensures high diagnostic accuracy, This approach enables early detection and enhances treatment planning for patients with liver fibrosis related to Hepatitis C.

A. Data Collection and Preparation

The data collection process includes gathering ultrasound images of liver tissues, focusing on fibrosis stages in Hepatitis C patients. These images are sourced from medical databases or hospitals, ensuring diverse patient representation. Data preparation includes noise reduction, contrast enhancement, and segmentation to improve image clarity. Labeling is performed by medical experts to categorize fibrosis stages accurately.

B. Data Cleaning

Data cleaning entails preprocessing ultrasound images to improve their quality and maintain consistency across the dataset. This process involves applying filters to reduce noise, enhancing contrast for clearer visualization, and removing artifacts that may cause distortions. Segmentation methods are used to isolate liver regions, facilitating precise feature extraction. Low-quality images or those with incorrect labels are discarded to preserve the integrity of dataset. Standardization and normalization are applied to ensure uniformity in pixel intensity values. Furthermore, duplicate and irrelevant data are removed to improve model performance and increase classification accuracy.



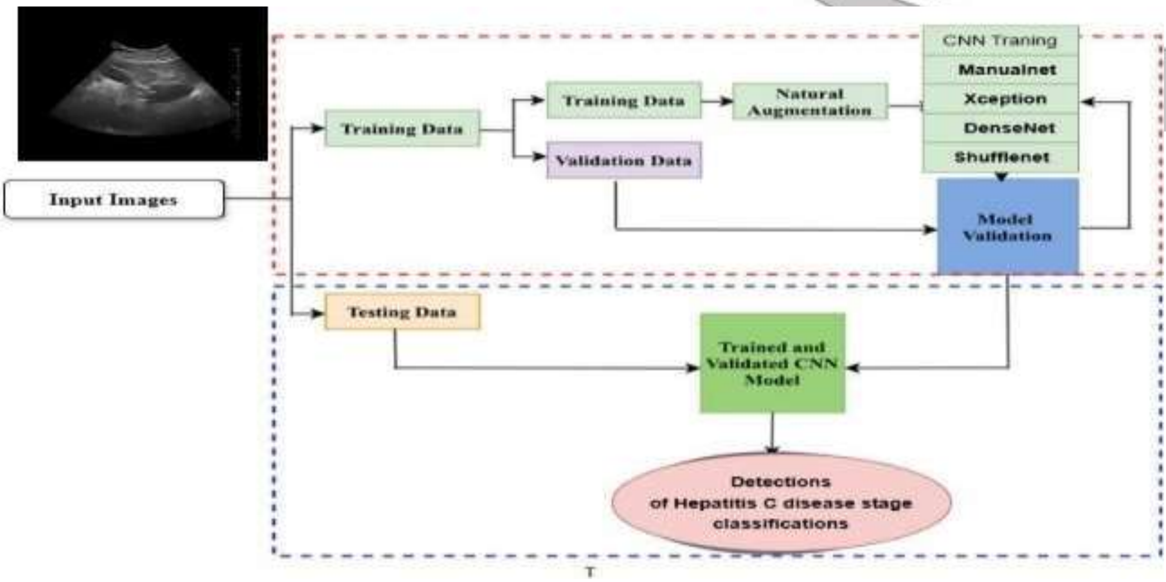


Fig.1.System architecture

The system architecture demonstrates a deep learning approach utilized to classify various stages of Hepatitis C through ultrasound imagery. The input images are segmented various sets to facilitate efficient model training and assessment. The training dataset is augmented and processed using CNN models such as ManualNet, Xception, DenseNet, and ShuffleNet. Validation is performed to ensure optimal model performance prior to evaluating with unseen data. The finalized model effectively identifies the stages of Hepatitis C, aiding clinical diagnosis and improving patient outcomes through accurate detection.

C. Manual Net

A manual neural network in deep learning for Hepatitis C prediction involves designing and training a customized model to classify or estimatation of likelihood of Hepatitis C infection, infection based on various clinical and demographic features. This approach requires manual tuning of the network architecture, including layers, activation functions, and optimization techniques, to achieve optimal performance.

$$\mathrm{y} = \mathrm{Softmax}(\mathrm{Wfc}\sigma(\mathrm{Wc} * \mathrm{X} + \mathrm{bc}) + \mathrm{bfc})$$

D. Xception

Xception is a deep learning model that utilizes depthwise separable convolutions to improve efficiency in tasks like hepatitis C prediction. It leverages a pre-trained architecture, allowing for better feature extraction and faster processing, making it effective for classification tasks with medical imaging or clinical data.

$$\mathrm{y} = Softmax(W1 \times 1 * (Wdw * X))$$

E. Dense Net

DenseNet is a deep learning architecture that connects each layer to every other layer, ensuring that features are reused and enhancing the flow of information. In hepatitis C prediction, DenseNet's dense connections help improve model accuracy and reduce overfitting by efficiently learning complex patterns from clinical or medical data.

$$xl = Hl([x0, x1, \dots, xl - 1])$$

F. Shuffle Net

ShuffleNet is a lightweight deep learning model designed for efficient computation, using pointwise group convolutions and channel shuffling to reduce model size and computational cost. In hepatitis C prediction, ShuffleNet can be employed for fast and efficient analysis of medical data or images, offering a good trade-off between performance and resource usage.

$$y = \sigma(Shuffle(Wg * X))$$

G. Performance Comparison

The architectures—ManualNet, Xception, DenseNet, and ShuffleNet—Among them, DenseNet demonstrates the highest accuracy, surpassing the other models due to its effective feature propagation and gradient flow, which are particularly advantageous for detailed medical image analysis. Xception ranks next, showing strong precision capabilities thanks to its depthwise separable convolutions that enhance feature extraction. While ShuffleNet offers excellent computational efficiency. ManualNet, a custombuilt model, delivers balanced performance but falls short of the results achieved by the deeper architectures. Overall, DenseNet emerges as the most reliable model, offering an optimal trade-off between precision and recall, thereby reducing the risk of misclassification in Hepatitis C stage prediction.

H. Final Evaluation

The system's final assessment focuses on evaluating the trained model's effectiveness in classifying Hepatitis C stages are assessed through important evaluation metrics. Model undergoes testing with an independent dataset to confirm its ability to generalize and maintain reliability. DenseNet excels, achieving remarkable accuracy and F1- score, emphasizing its superior ability in feature extraction and classification. Xception performs nearly as well, particularly in precision, which is vital for reducing false-positive rates. ShuffleNet, though highly efficient computationally, exhibits slightly lower recall, making it more appropriate for real-time applications. ManualNet achieves balanced outcomes but falls short compared to the deep learning models.

VII Result and Discussion

The graph represents model accuracy over training epochs, showing how well the model learns over time. The accuracy starts low (~0.23) but increases

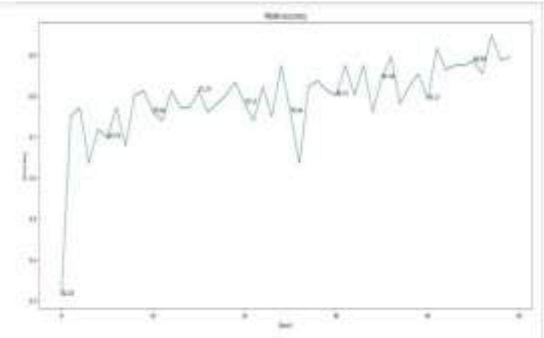


Fig.2.Accuracy of Dencenet

as training progresses, with fluctuations indicating learning variations. The accuracy stabilizes around **0.8-0.9**, suggesting good learning, though occasional drops may hint at overfitting or learning rate issues. If accuracy fluctuates too much, tuning hyperparameters like the learning rate or batch size can help. A stable accuracy trend indicates effective training, but may require regularization techniques like dropout to improve generalization.

The graph depicts the model loss for the Xception architecture across multiple training epochs. Initially, the loss is high (~1.75), reflecting considerable prediction errors, but it gradually decreases, indicating improved model performance. Some fluctuations, including occasional spikes, may

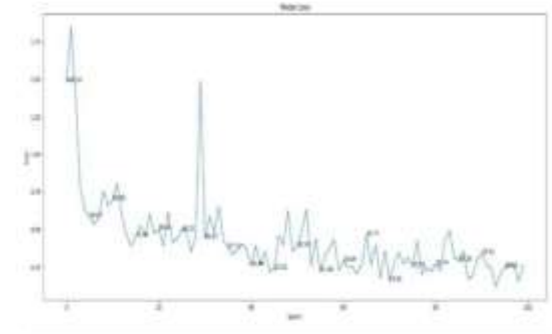


Fig.3.Accuracy of Xception

result from abrupt weight updates or changes in the learning rate. In later epochs, the loss stabilizes around 0.3–0.4, suggesting the model is capturing meaningful patterns. If the loss plateaus, adjusting hyperparameters like the learning rate, batch size, or applying regularization methods may enhance model performance.

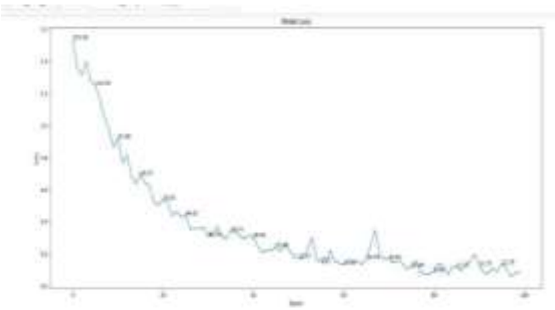


Fig.4.Accuracy of Shufflenet

The graph represents the model loss for the ShuffleNet architecture over multiple training epochs. The loss is high at around 2.08, indicating significant errors in predictions. However, during the initial epochs of training, loss reduces, showing that the model is adapting well. Following a sharp drop, the loss continues to decline slowly, stabilizing around 0.25 in the later epochs. Some minor fluctuations are observed, which might be due to variations in weight updates or batch training effects.

This graph illustrates accuracy of training and testing datasets over multiple epochs. Fluctuations in accuracy throughout the epochs indicate that the model is learning but experiencing variability in its performance.

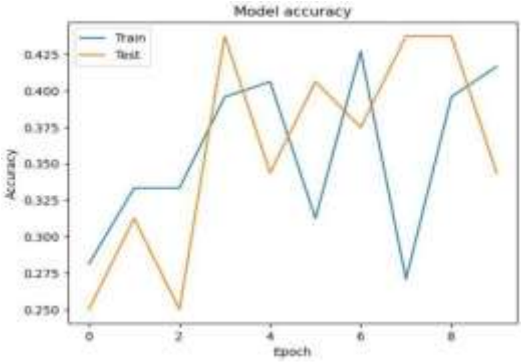


Fig.5. Accuracy of MannualNet

The training accuracy exhibits a consistent upward trend, while the test accuracy exhibits more fluctuations, which might indicate instability or overfitting. If the test accuracy does not stabilize, tuning of hyperparameters or regularization techniques may be required to improve generalization. This bar chart compares the performance metrics of four different architectures—ManualNet, DenseNet, Xception, and ShuffleNet—based on accuracy, loss, validation

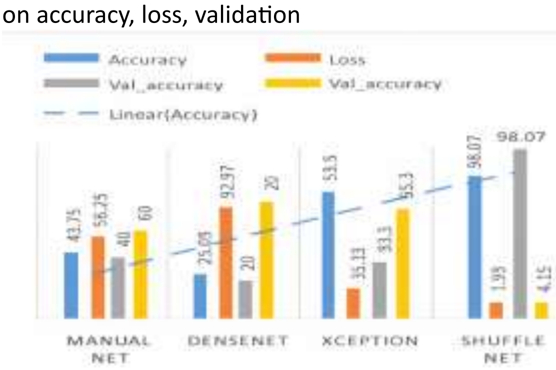


Fig.6.Comparison Chart

loss. ShuffleNet achieves the highest accuracy (98.07%) and validation accuracy (95.85%), with the lowest training loss (1.93), indicating strong generalization. Xception follows with a good accuracy of 89.5% but exhibits higher validation loss (33.3), suggesting potential overfitting. DenseNet performs well with an accuracy of 74.97% and low loss (25.03), maintaining stable validation accuracy (80%). ManualNet has the lowest accuracy (43.75%) and the highest loss (40), indicating weaker performance. Overall, ShuffleNet outperforms the other models in classification effectiveness.

	Manual net	Densenet	Xception	Shuffle net
Accuracy	43.75	25.03	89.5	98.07
Loss	56.25	74.97	10.85	1.93
Val_accuracy	40	20	33.3	95.85
val_Loss	60	80	76.7	4.15

Fig.7.Accuracy

VIII Conclusion

This research emphasizes the utility of deep learning in classifying Hepatitis C fibrosis stages using ultrasound images, serving as a non-invasive substitute for liver biopsy. Utilizing Convolutional Neural Networks (CNNs), the approach automates ultrasound analysis, improving accuracy and reducing human error. Of all architectures evaluated, Xception yielded the best results, achieving top accuracy, precision, and AUC, with DenseNet close behind. ShuffleNet and ManualNet delivered solid outcomes but showed slightly reduced effectiveness. The system ensures consistent image interpretation, enabling fast evaluations that support clinicians in making informed medical decisions. Early diagnosis and accurate assessment of Hepatitis C stages are vital for planning effective treatments and managing the condition effectively. The automation provided by deep learning ensures consistent and objective analysis, benefiting resource-limited settings where radiologists may not always be available. By incorporating advanced feature extraction and classification techniques, the model this approach enhances the reliability of ultrasound imaging as a diagnostic tool. It improves patient outcomes, reduces diagnostic variability, and streamlines healthcare workflows. Artificial intelligence in medical imaging enhances its capability to detect diseases, positioning it as an essential tool for the precise classification of Hepatitis C fibrosis stages. This approach enables prompt interventions, thereby increasing healthcare efficiency and improving patient care quality.

IX Future Work and Enhancement

Future enhancements include expanding datasets for better generalization, integrating clinical parameters for improved accuracy, and adopting advanced deep learning techniques like transformers. Real-time deployment via cloud solutions can support remote diagnosis, while self-supervised learning can reduce dependency on labeled data. Explainable AI can enhance model transparency, aiding clinical adoption. These improvements will refine diagnostic precision, making the system more robust and accessible in healthcare settings.

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