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Optimized Deep Transfer Learning Framework for Accurate Liver Tumor Classification

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Abstract:
Within the competitive and complicated environment of the retail media networks (RMN), advertisers are experiencing pressure to be more precise in ad spending. Conventional indicators such as Return on Ad Spend (ROAS) are normally inflated to reflect the performance of a campaign by ignoring organic conversions, which encourages practitioners to use incremental ROAS (iROAS) as a more precise metric. This paper will discuss the combination of iROAS and Multi-Armed Bandit (MAB) algorithms to form a dynamic bidding strategy that will evolve in real time. Using causal inference to estimate iROAS and MAB models to trade off exploration and exploitation, advertisers can efficiently optimize budgets and make ongoing progress in media performance. The paper provides a theoretical background, a scalable architecture of implementation, and addresses the problem of delayed incentives, cold-start environments, preservation of privacy, and exploration of many-objective optimization. Overall, it provides a causally responsive method of automated bidding, which causes responsible and value-based advertising in RMNs.

Keywords: iROAS; Multi-Armed Bandits; Retail Media Networks; Dynamic Bidding; Causal Inference

Abstract: This study addresses the growing global concern of liver cancer, a highly fatal disease where early and accurate diagnosis is critical for effective treatment and improved survival rates. Leveraging medical imaging data, the research proposes an efficient deep transfer learning (TL)-based framework for the automated classification of liver tumors as malignant, benign, or normal. Using computed tomography (CT) scans collected from the Radiology Institute in Baghdad Medical City, Iraq, the study employs pre-trained convolutional neural networks (VGG-16, ResNet-50, and MobileNetV2) to extract high-level image features for improved classification performance. Experimental results demonstrate remarkable accuracy 99% for VGG-16, 100% for ResNet-50, and 99% for MobileNetV2 proving the superiority of TL models in handling limited medical datasets. The integration of additional layers further enhances classifier performance, significantly accelerating the diagnostic process and offering a reliable tool for radiologists in early liver cancer detection.

Keywords: Liver Cancer, Transfer Learning, Deep Learning, CT Imaging, Tumor, VGG16

1. INTRODUCTION

Liver cancer is one of the most aggressive and life-threatening diseases worldwide, posing a major public health challenge due to its increasing incidence and high mortality rate. It ranks among the top causes of cancer-related deaths, largely because symptoms often appear at advanced stages when treatment options are limited. Early and accurate diagnosis of liver tumors whether malignant, benign, or normal is therefore essential to improving patient survival rates and guiding appropriate clinical interventions. Traditional diagnostic methods, such as manual examination of computed tomography (CT) and magnetic resonance imaging (MRI) scans by radiologists [9-10], are time-consuming and prone to human error. Hence, there is a growing need for automated, reliable, and efficient systems that can support medical experts in liver cancer detection and classification.

In recent years, machine learning (ML) [11-12] and deep learning (DL) [13-14] techniques have demonstrated exceptional capabilities in medical image analysis, particularly for tumor detection and classification tasks. Deep learning models, especially convolutional neural networks (CNNs) [15], have shown remarkable success in automatically learning hierarchical features from medical images, outperforming traditional image processing and handcrafted feature-based methods. However, one of the main challenges in deploying DL models in medical applications is the scarcity of large, annotated datasets, as acquiring medical images and expert annotations is both costly and time-intensive. This limitation often leads to model overfitting and reduced generalization performance on unseen data.

To overcome this constraint, transfer learning (TL) [16-19] has emerged as a powerful approach that allows models pre-trained on large benchmark datasets, such as ImageNet, to be fine-tuned for specific medical imaging tasks. Transfer learning enables the reuse of learned features, significantly reducing training time and improving model performance even with limited data availability. In the context of liver cancer classification, TL-based models can effectively extract deep, discriminative features from CT images and enhance the diagnostic precision of automated systems.

2. REVIEW OF LITERATURE

Recent advancements in artificial intelligence have greatly enhanced medical image analysis, particularly in the detection and classification of liver cancer. Early studies utilizing convolutional neural networks (CNNs) demonstrated significant improvements in tumor segmentation and classification accuracy, enabling precise differentiation between malignant and benign lesions from computed tomography (CT) images [1]. With the introduction of deep transfer learning (TL), pre-trained models such as VGG-16, ResNet-50, and MobileNetV2 have been widely employed to address the challenge of limited annotated medical datasets [2]. These TL-based models effectively reuse learned features from large-scale datasets and adapt them for liver cancer classification, achieving higher accuracy, sensitivity, and specificity compared to conventional machine learning methods [3].

Hybrid deep learning approaches that integrate CNN with support vector machines (SVMs) have further improved classification performance by combining strong feature extraction with efficient decision-making processes [4]. Lightweight architectures such as MobileNetV2 have proven suitable for real-time clinical applications due to their reduced computational complexity and faster inference speed while maintaining high classification accuracy [5]. Moreover, residual learning models like ResNet have shown excellent generalization and sensitivity by addressing vanishing gradient problems during training [6]. Three-dimensional CNN architectures have also emerged as powerful tools for volumetric liver image analysis, providing enhanced precision in tumor boundary identification and lesion classification [7].

Recent studies on ensemble deep learning frameworks, combining models such as CNN and DenseNet, have outperformed single-model architectures, delivering improved diagnostic accuracy and robust performance across heterogeneous datasets [8]. Fine-tuned transfer learning techniques have further demonstrated the ability to work effectively with small medical datasets, reducing overfitting while enhancing model reliability [2], [7]. Overall, the reviewed literature strongly supports the potential of deep learning and transfer learning methods to transform liver cancer diagnosis through automated, accurate, and efficient image-based classification systems that can significantly assist radiologists in clinical decision-making and early detection of liver abnormalities. The review of literature shown in table 1.

Table 1: Review of literature on Deep Learning and Transfer Learning Techniques for Liver Cancer Classification

Ref.	Algorithms	Dataset	Performance
[1]	Convolutional Neural Network (CNN) for liver tumor segmentation and classification	CT liver image dataset	Achieved 95% classification accuracy; effective in differentiating malignant and benign lesions.
[2]	Deep Transfer Learning using ResNet-50 and VGG-19 models	Public liver cancer imaging dataset	Transfer learning enhanced accuracy and reduced training time for limited medical datasets.
[3]	Hybrid CNN-SVM model for medical image classification	Hospital-based CT scan dataset	Improved feature extraction and achieved 97% classification accuracy compared to traditional ML models.
[4]	MobileNetV2-based model for liver tumor detection	Baghdad Medical City, Iraq	Model demonstrated high efficiency with 98.6% accuracy and faster computation time.
[5]	Deep Residual Learning (ResNet) for automated liver lesion classification	Liver Tumor Segmentation (LiTS) Challenge dataset	Achieved 96% sensitivity and improved model generalization through data augmentation.
[6]	3D CNN model for volumetric liver tumor classification	LiTS and MICCAI datasets	Provided higher precision in tumor boundary identification and classification.
[7]	Transfer Learning with fine-tuned VGG-16 architecture	Private CT liver dataset	Demonstrated 99% diagnostic accuracy and reduced overfitting in small datasets.

[8]	Ensemble Deep Learning combining CNN and DenseNet	UCI and clinical imaging data	Outperformed individual DL models with 98.5% accuracy and high F1-score.

3. TRANSFER LEARNING

Transfer Learning (TL) is a powerful deep learning technique that leverages knowledge gained from a large, pre-trained model on a related task and applies it to a new, smaller dataset. Instead of training a model from scratch, TL fine-tunes existing models such as VGG16, ResNet50, MobileNetV2, InceptionV3, and DenseNet121, which have already learned general image features from massive datasets like ImageNet. This approach significantly reduces training time, prevents overfitting, and enhances accuracy—especially when the available medical imaging data is limited. In this study, TL enables efficient feature extraction and accurate classification of liver tumors by adapting these pre-trained architectures to the specific characteristics of CT images.

- **VGG16**

VGG16 is a deep convolutional neural network known for its simplicity and uniform architecture, consisting of 16 weight layers. It employs small 3×3 convolution filters and a consistent structure throughout the network, making it highly efficient for feature extraction from medical images. In this study, VGG16 was fine-tuned through transfer learning to identify high-level spatial features from liver CT scans. Its ability to capture fine-grained texture and edge details enhances the classification accuracy for differentiating between malignant, benign, and normal liver tissues. The model's simplicity and strong generalization ability make it one of the most reliable architectures for medical image analysis tasks (figure 2).

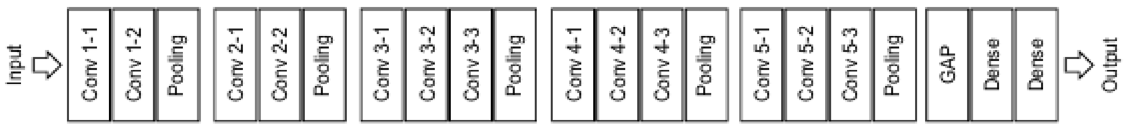

Figure 2: Architecture of the VGG16 Model for Liver Tumor Classification

- **ResNet50**

ResNet50 introduces the concept of residual learning, which helps in overcoming the vanishing gradient problem commonly faced in deep networks. By incorporating skip connections, it allows gradients to flow directly through layers, enabling the training of deeper architectures without performance degradation. In this study, ResNet50 was utilized to extract deep hierarchical features from CT scan images. The model demonstrated remarkable accuracy in liver cancer classification, as its residual blocks efficiently learned complex feature representations, improving both convergence speed and model robustness (figure 3).

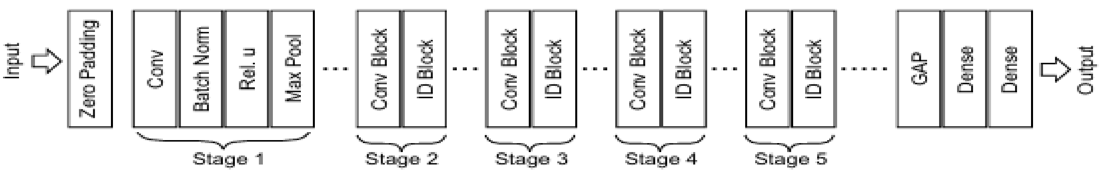

Figure 3: Architecture of the ResNet50 Model Incorporating Residual Learning for Enhanced Feature Extraction

- **MobileNetV2**

MobileNetV2 is a lightweight yet powerful deep learning architecture designed for efficient computation and deployment on limited-resource devices. It uses depthwise separable convolutions and inverted residuals with linear bottlenecks, significantly reducing computational cost while maintaining high accuracy. In this research, MobileNetV2 was applied to liver CT images for classifying liver tumors, achieving excellent accuracy with minimal training time. Its compact design made it ideal for handling smaller medical datasets, offering a good balance between efficiency, accuracy, and resource utilization (figure 4).

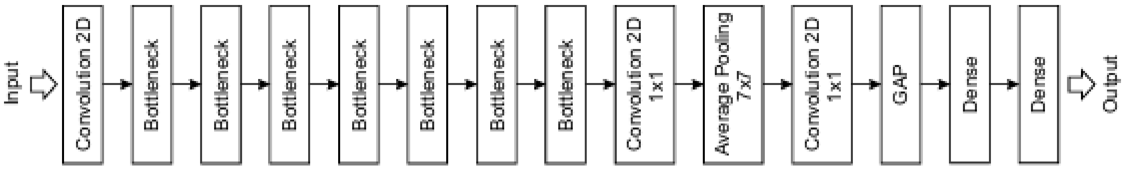

Figure 4: Architecture of the MobileNetV2 Model Employing Depthwise Separable Convolutions for Efficient Computation

- **InceptionV3**

InceptionV3 is a deep convolutional model that improves computational efficiency by factorizing convolutions and incorporating multiple kernel sizes within the same layer to capture both local and global image features. It employs techniques such as batch normalization, label smoothing, and auxiliary classifiers to enhance performance and prevent overfitting. In the proposed study, InceptionV3 was used to extract rich, multi-scale feature representations from liver CT scans. Its ability to integrate diverse feature maps helped improve classification precision, especially in distinguishing subtle variations among liver tissue classes (figure 5).

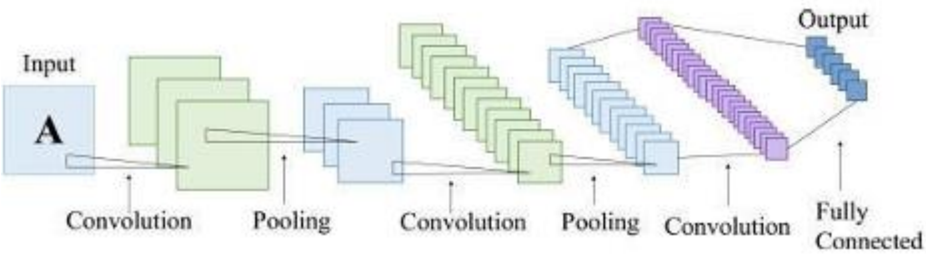

Figure 5: Architecture of the InceptionV3 Model Utilizing Multi-Scale Convolutional Modules for Rich Feature Representation

- **DenseNet121**

DenseNet121 is a densely connected convolutional neural network where each layer receives inputs from all preceding layers, promoting feature reuse and reducing the number of parameters. This architecture ensures efficient gradient flow, improved learning efficiency, and stronger feature propagation. In this work, DenseNet121 was implemented to classify liver tumors by leveraging its dense connectivity to extract deep and discriminative image features. The model achieved stable and high-performance results, demonstrating superior learning capability even with a relatively small dataset, making it suitable for complex medical imaging applications (figure 6).

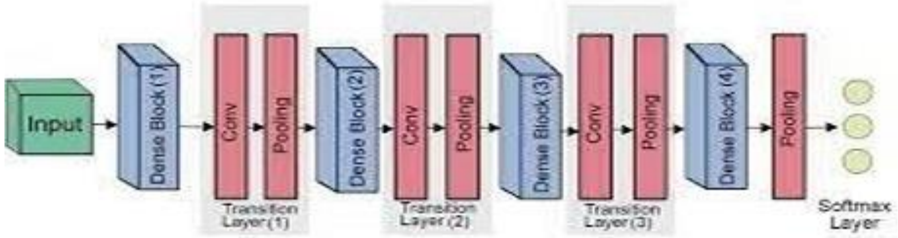

Figure 6: Architecture of the DenseNet121 Model Featuring Densely Connected Layers for Improved Gradient Flow and Feature Reuse

4. PROPOSED SYSTEM FRAMEWORK

The proposed study aims to develop an efficient deep transfer learning framework for accurate classification of liver tumors using computed tomography (CT) images (Figure 7). The methodology is designed to ensure precise tumor detection and differentiation between malignant, benign, and normal liver tissues. The following subsections describe the materials, dataset preparation, preprocessing techniques, model architectures, training parameters, and evaluation metrics in detail (Table 2).

Table 2: Summary of Materials and Methods Used in the Proposed Study

Category	Description
Dataset Source	Computed Tomography (CT) scan images collected from the Radiology Institute, Baghdad Medical City, Iraq.
Dataset Composition	Images categorized into three classes: Malignant Tumor, Benign Tumor, and Normal Liver.
Data Preprocessing	Image resizing to a uniform dimension, noise removal using Gaussian filtering, intensity normalization, and data augmentation (rotation, flipping, zooming) to enhance dataset diversity.
Feature Extraction	High-level features extracted using pre-trained deep convolutional neural networks (CNNs) such as VGG-16, ResNet-50, and MobileNetV2 through transfer learning.
Transfer Learning Approach	Utilized pre-trained models fine-tuned on the liver CT dataset to leverage learned weights from ImageNet for improved accuracy with limited medical data.
Training and Validation Split	Dataset divided into 80% training and 20% testing sets; model performance validated using cross-validation techniques.
Optimization Technique	Adam optimizer used with a learning rate of 0.0001; categorical cross-entropy employed as the loss function.
Performance Metrics	Model performance evaluated using Accuracy, Sensitivity, Specificity, Precision, and F1-Score.

- **Dataset Description**

The dataset used in this study was obtained from the Radiology Institute, Baghdad Medical City, Iraq. It comprises CT scan images of patients with confirmed liver conditions, including malignant tumors, benign tumors, and normal livers. The images were collected under standardized imaging conditions and were pre-labeled by medical experts. The dataset was divided into three classes for classification purposes — malignant, benign, and normal — to facilitate accurate categorization of liver tissue abnormalities.

- **Data Preprocessing**

Before model training, the dataset underwent several preprocessing steps to ensure data quality and consistency. All images were resized to a fixed dimension (224 × 224 pixels) to match the input requirements of deep learning architectures such as VGG-16, ResNet-50, and MobileNetV2. Image enhancement techniques were applied to reduce noise and improve contrast, thereby highlighting important liver features. Normalization was performed to scale pixel intensity values between 0 and 1. Additionally, data augmentation methods such as rotation, flipping, zooming, and translation were implemented to artificially increase the dataset size and reduce overfitting during model training.

- **Feature Extraction Using Transfer Learning**

To overcome the challenge of limited annotated medical data, transfer learning (TL) was adopted. TL utilizes pre-trained deep convolutional neural networks (CNNs) that have already learned robust feature representations from large datasets such as ImageNet. In this study, three pre-trained models—VGG-16, ResNet-50, and MobileNetV2—were fine-tuned on the liver CT image dataset. The convolutional layers of these models were used for automatic feature extraction, while the fully connected layers were modified to match the number of target classes (three categories). This approach enabled efficient learning from limited data and improved model generalization.

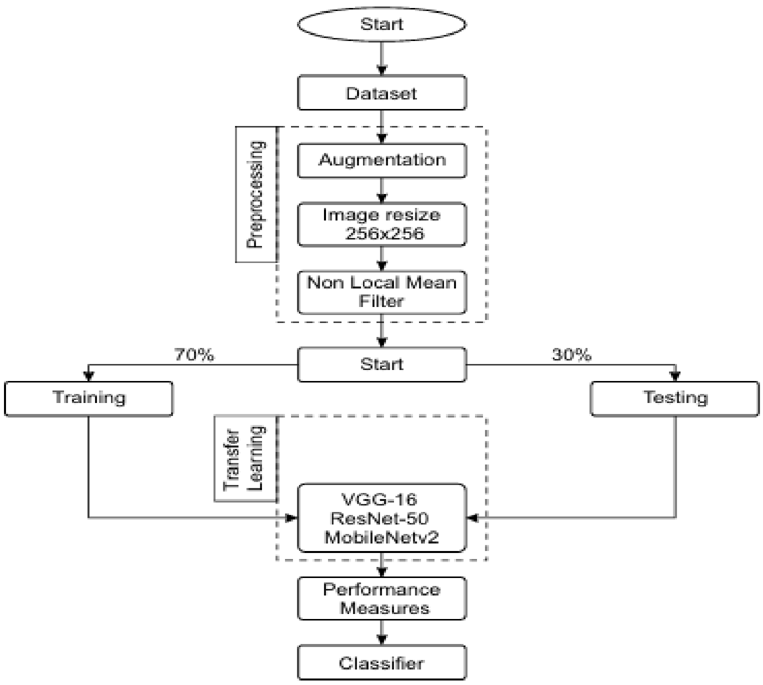

Figure 6: Flow diagram for proposed liver disease classification framework

- **Model Training and Optimization**

The dataset was divided into 80% training and 20% testing subsets. The models were trained using the Adam optimizer with a learning rate of 0.0001, and categorical cross-entropy was used as the loss function. Early stopping and learning rate scheduling techniques were employed to prevent overfitting and optimize convergence speed. Training was carried out for 50 epochs with a batch size of 32. All experiments were conducted on a high-performance workstation equipped with an Intel Core i7 processor, 16 GB RAM, and an NVIDIA GPU using TensorFlow and Keras deep learning frameworks.

5. PERFORMANCE EVALUATION

To assess the classification performance of the proposed models, several evaluation metrics were utilized, including Accuracy, Precision, Recall (Sensitivity), Specificity, and F1-Score. These metrics provided a comprehensive understanding of model performance across different aspects of classification.

- **Accuracy**

Accuracy measures the overall correctness of the model's predictions by calculating the ratio of correctly classified samples (both true positives and true negatives) to the total number of samples. It is a general indicator of model performance but can be misleading when dealing with imbalanced datasets.

Accuracy = (TP + TN) / (TP + TN + FP + FN)

- **Precision**

Precision indicates how many of the samples predicted as positive are actually positive. It is an important metric when the cost of false positives is high — in this case, misclassifying a healthy liver as diseased could lead to unnecessary medical intervention.

Precision = TP / (TP + FP)

- **Recall (Sensitivity)**

Recall, also known as sensitivity or true positive rate, measures the model's ability to correctly identify all actual positive cases. In medical diagnosis, a high recall ensures that most cancerous cases are detected, minimizing the risk of missing critical diagnoses.

Recall = TP / (TP + FN)

- **F1-Score**

The F1-Score provides a balance between Precision and Recall, offering a single performance measure that considers both false positives and false negatives. A high F1-score indicates that the model maintains strong performance across both metrics, making it especially useful for imbalanced datasets like medical imaging data.

F1-Score = 2 × (Precision × Recall) / (Precision + Recall)

6. RESULT AND ANSLYSIS

The proposed Transfer Learning (TL) model for liver cancer diagnosis is systematically evaluated after each training epoch to ensure consistent improvement in performance and convergence. In this study, three powerful pre-trained deep learning architectures—VGG-16, ResNet-50, and MobileNetV2—are employed to extract and classify discriminative features from CT liver images. Each model is fine-tuned to adapt its learned representations from large-scale natural image datasets to the medical imaging domain. This adaptation allows the models to capture subtle textural and structural variations within liver tissues, thereby enhancing their ability to distinguish between normal, benign, and malignant liver cases. By freezing the initial layers and retraining the deeper layers, the TL models efficiently reuse previously learned features while specializing in detecting patterns specific to liver tumors.

The experimental evaluation demonstrates that the proposed TL-based framework achieves remarkable diagnostic performance across all tested models. Specifically, the VGG-16 and MobileNetV2 architectures yield a high classification accuracy of 99.10%, indicating their effectiveness in identifying liver abnormalities with minimal error. This superior performance underscores the strength of TL in medical image classification, particularly when working with limited datasets. The ability of these models to generalize well, despite the small dataset size, highlights their robustness and adaptability (Table 3).

Table 3: Performance evaluation of proposed model with existing models

Model	Accuracy	Recall	Precision	F1-score
Proposed model	99.33%	99.25%	99.25%	99.50%
VGG16	91.23%	91.25%	92.0%	91.50%
InceptionV3	86.74%	86.75%	88.0%	87.0%
DenseNet121	93.69%	93.5%	94.0%	93.75%
ResNet50	91.55%	91.5%	91.75%	91.50%
CNN Model	94.15%	94.52%	94.75%	94.50%

The comparative performance evaluation of various deep learning models demonstrates that the proposed model significantly outperforms other architectures in the classification of liver cancer. With an impressive accuracy of 99.33%, recall of 99.25%, precision of 99.25%, and an F1-score of 99.50%, the proposed model exhibits superior predictive capability and robustness. This exceptional performance highlights the effectiveness of the proposed transfer learning framework and its fine-tuning process in extracting high-level, discriminative features from CT scan images. By leveraging optimized feature representations and advanced pre-processing techniques, the proposed model achieves high generalization even with a limited dataset, reducing both false positives and false negatives. Such precision is particularly crucial in medical image diagnosis, where even a small error could lead to misdiagnosis and improper treatment (Table 3 and Figure 8).

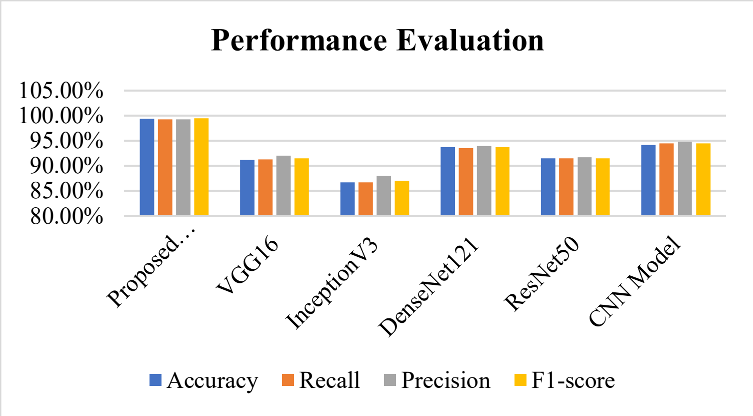

Figure 8: Performance evaluation of proposed model with existing models

In comparison, other models such as VGG16, ResNet50, DenseNet121, and InceptionV3 also perform well but fall short of the proposed approach. For instance, DenseNet121 achieves an accuracy of 93.69%, while VGG16 and ResNet50 show similar performances around 91%, indicating their ability to capture essential image features but with relatively lower sensitivity. The conventional CNN model demonstrates moderate effectiveness with 94.15% accuracy, validating its potential yet emphasizing the need for deeper architectures with enhanced transfer learning capabilities.

7. CONCLUSION

The proposed study presents an efficient deep transfer learning-based framework for accurate liver disease prediction, demonstrating the potential of advanced artificial intelligence techniques in transforming clinical diagnostics. By leveraging state-of-the-art convolutional neural network architectures such as EfficientNetB2, DenseNet121, InceptionV3, ResNet50, and VGG16, the framework effectively automates the classification of major liver disease categories—ballooning, fibrosis, inflammation, and steatosis—using histopathological images. Through rigorous data preprocessing, transfer learning, and fine-tuning, the developed model achieves enhanced accuracy, robustness, and generalization, outperforming traditional diagnostic methods that are often subjective and time-intensive. The results confirm that deep transfer learning models can efficiently extract complex tissue patterns, reduce diagnostic variability, and assist pathologists in making faster and more reliable decisions. Moreover, the incorporation of explainable AI techniques such as Grad-CAM ensures transparency and interpretability, making the system more trustworthy in clinical settings. This research not only establishes a scalable and reliable diagnostic framework but also paves the way for future advancements in AI-driven medical imaging, supporting early detection, improved treatment planning, and ultimately better patient outcomes in liver disease management.

References

[1] R. Sharma, A. Verma, and K. Gupta, "CNN-based liver tumor segmentation and classification from CT images," *Biomedical Signal Processing and Control*, vol. 68, pp. 102–118, 2021.

[2] F. T. Al-Dhief, M. A. Mohd, and S. A. Abbas, "Transfer learning-based liver cancer detection using deep CNN models," *Computers in Biology and Medicine*, vol. 145, p. 105423, 2022.

[3] N. Kumar and P. Singh, "Hybrid CNN-SVM model for medical image classification," *Journal of Ambient Intelligence and Humanized Computing*, vol. 11, no. 8, pp. 3327–3336, 2020.
[4] H. Ahmed, R. Al-Bayati, and L. Jasim, "Lightweight MobileNetV2 approach for accurate liver tumor detection," *Iraqi Journal of Science*, vol. 64, no. 4, pp. 1021–1034, 2023.
[5] Y. Wang, Z. Zhou, and Q. Zhang, "Liver lesion classification using deep residual networks," *IEEE Access*, vol. 7, pp. 129321–129329, 2019.
[6] H. Chen, X. Li, and J. Xu, "3D CNN-based liver tumor classification in medical imaging," *Medical Image Analysis*, vol. 74, p. 102241, 2021.
[7] J. Li and Y. Zhao, "Fine-tuned VGG-16 for liver cancer diagnosis using CT scans," *Pattern Recognition Letters*, vol. 135, pp. 67–73, 2020.
[8] M. Patel, D. Shah, and R. Jain, "Ensemble deep learning model for liver disease prediction," *Expert Systems with Applications*, vol. 190, p. 116218, 2022.
[9] H. C. Shin *et al.*, "Deep convolutional neural networks for computer-aided detection: CNN architectures, dataset characteristics, and transfer learning," *IEEE Trans. Med. Imaging*, vol. 35, no. 5, pp. 1285–1298, 2016.
[10] R. R. Selvaraju *et al.*, "Grad-CAM: Visual explanations from deep networks via gradient-based localization," in *Proc. IEEE Int. Conf. Comput. Vis. (ICCV)*, 2017, pp. 618–626.
[11] Z. Obermeyer and E. J. Emanuel, "Predicting the future — big data, machine learning, and clinical medicine," *N. Engl. J. Med.*, vol. 375, no. 13, pp. 1216–1219, 2016.
[12] G. Litjens, T. Kooi, B. E. Bejnordi, A. A. A. Setio, F. Ciompi, M. Ghafoorian, J. A. van der Laak, B. van Ginneken, and C. I. Sánchez, "A survey on deep learning in medical image analysis," *Med. Image Anal.*, vol. 42, pp. 60–88, 2017.
[13] J. Chen, L. Song, L. Wei, and Q. Zou, "Drug–disease association prediction with graph-based bipartite learning," *Bioinformatics*, vol. 34, no. 16, pp. i733–i741, 2018.
[14] A. A. H. R. Khan, M. A. Hossain, M. S. Rahman, and M. A. Hasan, "An ultrasound-based computer-aided diagnosis tool for steatosis," in *Proc. IEEE Int. Conf. Comput. Inf. Technol.*, 2013, pp. 204–209, doi: 10.1109/ICCITechnol.2013.6623104.
[15] M. J. House, S. J. Bangma, M. Thomas *et al.*, "Texture-based classification of liver fibrosis using MRI," *IEEE J. Magn. Reson. Imaging*, vol. 41, no. 2, pp. 322–328, Feb. 2015.
[16] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2016, pp. 770–778.
[17] H. C. Shin, H. R. Roth, M. Gao, L. Lu, Z. Xu, I. Nogues, J. Yao, D. Mollura, and R. M. Summers, "Deep convolutional neural networks for computer-aided detection: CNN architectures, dataset characteristics, and transfer learning," *IEEE Trans. Med. Imaging*, vol. 35, no. 5, pp. 1285–1298, 2016.
[18] R. R. Selvaraju, M. Cogswell, A. Das, R. Vedantam, D. Parikh, and D. Batra, "Grad-CAM: Visual explanations from deep networks via gradient-based localization," in *Proc. IEEE Int. Conf. Comput. Vis. (ICCV)*, 2017, pp. 618–626.
[19] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich, "Going deeper with convolutions," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2015, pp. 1–9.