

MED-RESATTXNET: A HYBRID DEEP LEARNING FRAMEWORK FOR DETECTION AND CLASSIFICATION OF LIVER DISEASES USING BIOMEDICAL IMAGE ANALYSIS

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ABSTRACT

Liver diseases remain one of the most critical public health challenges worldwide, contributing significantly to mortality and long-term disability. Early and accurate diagnosis is central to successful treatment, but traditional methods involving biopsy and manual analyses of images present many problems, including invasiveness, inconsistency and delay. This paper presents Med-ResAttXNet as a hybrid cell that incorporates three complementary cells: the attention-augmented U-Net++ to segment liver and lesions, the Residual Attention Network to focus feature learning, and Vision Transformer to learn a global context. These modules are integrated as part of a single pipeline, which then classify liver conditions as being healthy, benign and malignant. The main idea behind the presented work is that properly architected hybrid scheme may surpass traditional CNN-based or standalone models and take the best of both worlds, offering both local accuracy and broader context. Compared to existing methods on a publicly-available liver tumor segmentation dataset (LiTS), the proposed model demonstrated the highest score in segmentation accuracy and Dice coefficient, in addition to classification measures, validating the effectiveness and potential of the proposed model in clinical applications. This sample proves that Med-ResAttXNet can be a reliable decision-support tool that will help radiologists make an early diagnosis and plan the treatment.

Keywords: *Residual Attention Network, Vision Transformer, Medical Image Segmentation, U-Net++, Hybrid Deep Learning Architecture, CT Scan Classification, Med-ResAttXNet.*

1. INTRODUCTION

Liver diseases are a significant contributor to the worldwide health load, and millions of people are exposed each year to such liver problems as fatty liver, hepatitis, cirrhosis, and hepatocellular carcinoma [1], [3]. What makes the problematic is not just the silent advancement of most of such diseases but also the fact that most of these diseases are difficult to diagnose at the early stages thereby leaving little avenues in terms of treatment and prognosis [2], [5]. The existing methods of diagnosis such as the biopsy, biochemical and direct physical view of CT or MRI scans, are either invasive or depend heavily on the expertise of the radiologists [6], [10]. This reliance adds unpredictability to the interpretation and raises the risk of late, or erroneous decision making, especially in areas where trained specialists are few [9], [11].

Artificial intelligence, and deep learning in particular, has come to revolutionize medical image analysis as it provides a model-free means of extracting patterns and identifying anomalies without the need of clusterable manual labor [4], [7]. CNNs have successfully been used to perform liver imaging; nevertheless, these models fail to learn long-range dependencies, which is critical in interpreting complicated liver diseases [15], [20]. On the same note, segmentation models such as U-Net++ are excellent in lesion identification but are poor in classification when used alone [13]. Transformers, on the other hand have demonstrated appropriateness in modelling global image context, but fail to perform well when considering fine-grained localization tasks when not applied in combination [17].

This gap presents the necessity of a single framework in which the advantages of both these architectures can be merged. The main idea of this

study, as far as hypotheses are concerned, is that an integrated hybrid scheme of segmentation, specialized feature extraction, and overall context learning will be able to enhance the accuracy and stability of liver disease detection substantially over and above single models. To speculate this hypothesis, we introduce Med-ResAttXNet, a compound architecture that incorporated Attention-based U-Net++ to segmentation, Residual Attention Networks on feature refinement and Vision Transformers on contextual representation [12], [14], [18]. The framework is validated on the Liver Tumor Segmentation (LiTS) dataset, demonstrating superior diagnostic performance and highlighting its potential as a clinically useful tool [16], [19].

The structure of the rest of the paper is as follows: Section II has a review of related works and significant contributions in liver disease detection and medical image classification. The section III further explains the proposed methodology, stating the components of the Med-ResAttXNet framework. Section IV is concerned with the dataset and preprocessing methods. The experimental setup and evaluation metrics are provided in Section V. Section VI presents the results and comparative analysis, followed by conclusions and future work in Section VII.

2. LITERATURE REVIEW

Recent advances in artificial intelligence and biomedical imaging have accelerated progress in the diagnosis of liver diseases. Traditional diagnostic workflows, which rely on tissue biopsies and manual interpretation by medical experts, are gradually being supplemented or replaced by automated, data-driven approaches based on deep learning [6], [7]. These modern methods overcome the limitations of manual feature extraction, which is often subjective and struggles with the high variability of patient data [14], [19].

Convolutional Neural Networks (CNNs) have been central to medical image analysis for over a decade, demonstrating strong performance in tasks such as spatial localization and disease detection through hierarchical feature learning [3], [14], [18]. CNNs have a limitation with regards to modeling global dependencies and hence will not find much use in understanding what are the complex disease patterns. To resolve this, U-Net, and its improved versions like U-Net++ have been produced. U-Net++ adds dense skip connections to enhance multi-scale feature learning, and is especially

effective when used in medical image segmentation tasks [10], [13].

Attention mechanisms have also enhanced the performances of CNN. To provide an illustrative example, Residual Attention Networks (ResAttNet) unify the concepts of residual learning and spatial and channel-wise attention, enabling models to identify the most important details of medical scans to eliminate noise in the background [11], [12]. This is especially crucial with liver disease analysis, wherein lesion boundaries may be weak or abnormal [14], [19].

Transformer-based models are the more recent paradigm innovations in the medical imaging domain. ViTs, originally trained to work with natural images, have shown the potential of learning long-range dependencies and achieve contextual patch understanding [4], [5], [17]. CNNs are complementary to such global modeling, and can be beneficial in the context of complex presentations such as hepatocellular carcinoma or metastatic liver tumors [15], [20].

Although U-Net++, ResAttNet and ViTs have demonstrated success on their own, they have not been incorporated into a complete pipeline with limited research on the subject matter of liver disease diagnosis. However, hybrid designs that combine segmentation, attention-based feature enhancement and transformer-based global context representation could enhance the robustness and generalization that can be learned across many datasets [8], [9], [16]. Moreover, lightweight and flexible deep learning could be used as one more important step in deploying deep learners into resource-limited clinical settings, the need to use scalable and transparent models [1], [2].

This review demonstrates that biomedical AI has reached an emerging consensus that requires multiple models to be used to achieve clinically meaningful results. Rather, hybrid-based approaches; combining complementary methods (efficient segmentation (U-Net++), attention-based feature extraction (ResAttNet), and contextual representation (ViTs)) can provide a better solution. To address this requirement, the new Med-ResAttXNet end-to-end hybrid architecture is proposed to better the specificity and confidence of liver disease identification on the basis of CT image data.

2.1 Problem Statement

Liver diseases are seen as a major cause of morbidity and mortality across the world. Their predominant issue is their late/improper diagnosis, which is attributable to invasive tests and the interpretation of medical images which is subjective in nature. Current imaging-based diagnostics are heavily dependent on radiologists, which leads to variability in assessment and potential misdiagnosis. In addition, the complexity and heterogeneity of biomedical imaging data make it difficult to detect subtle indicators of liver disease at an early stage.

There is therefore a pressing need for a reliable and efficient diagnostic system capable of automatically detecting and classifying liver diseases from medical images. Current AI approaches often focus exclusively on either segmentation or classification, failing to leverage the potential of an integrated end-to-end pipeline.

2.2 Research Question

Can a hybrid deep learning framework that integrates segmentation, attention-based feature extraction, and transformer-based contextual modeling outperform existing standalone models in improving the accuracy and reliability of liver disease detection?

2.3 Objective

The study aims to design and evaluate *Med-ResAttXNet*, a hybrid deep learning architecture for liver disease diagnosis using CT scan images. The key objectives are:

1. To segment liver and lesion regions accurately using an improved Attention-based U-Net++ [10], [13].
2. To extract discriminative features using Residual Attention Networks, emphasizing disease-specific regions [11], [14].
3. To integrate global contextual information using Vision Transformers for enhanced classification [4], [5], [17].
4. To fuse features from segmentation and attention modules through a multi-layer perceptron (MLP) for final classification into healthy, benign, and malignant

categories

[9],

[15].

5. To validate the proposed model against CNN-based baselines using the LiTS dataset, evaluating accuracy, Dice scores, and AUC-ROC [7], [19].

2.4 Scope of the Study

This research focuses on CT scan-based liver disease diagnosis using deep learning techniques. The framework covers the entire pipeline—segmentation, feature extraction, contextual modeling, and classification. The study is limited to CT imaging; other modalities such as MRI or ultrasound are not considered in this work. Clinical validation is beyond the current scope, though the framework is intended for future adaptation to clinical use [8], [19], [20].

2.5 Author Contribution

- **Conceptualization and Design:** Development of the hybrid Med-ResAttXNet architecture.
- **Data Curation and Preprocessing:** Implementation of standard biomedical imaging preprocessing methods.
- **Model Implementation:** Development of segmentation, feature extraction, and classification modules.
- **Performance Evaluation:** Benchmarking against existing CNN and hybrid methods using robust validation strategies.
- **Manuscript Preparation:** Drafting technical sections according to academic publication standards.

3. MATERIALS AND METHODS

This section describes the dataset, preprocessing pipeline, model architecture, training procedures, and evaluation metrics used to develop and validate the proposed Med-ResAttXNet framework.

3.1 Dataset

The Liver Tumor Segmentation (LiTS) Challenge dataset [6] was used for this study. The

dataset consists of 131 contrast-enhanced abdominal CT scans with corresponding ground-truth annotations for liver and tumor segmentation [14]. Each scan is provided in DICOM or NIfTI format and includes volumetric data with detailed annotations of:

- Whole liver boundaries
- Tumor lesion regions

3.2 Data Preprocessing

The dataset includes diverse cases, covering multiple stages and types of liver disease such as hepatocellular carcinoma and metastatic lesions. The variation in lesion size, shape, and contrast provides robustness to the training process and supports model generalization.

Performance is also homogenized, i.e. all scans are re-sampled into a uniform voxel spacing.

- Intensity normalization is performed in the window of Hounsfield Unit (HU) from -200 to 250.
- Liver region cropped from the 3D scan with the use of ground-truth masks to fasten computation.
- Slices having lesions are enriched by applying stratified sampling for an equal representation.

The dataset was split into training, validation and testing set with ratio 80:10:10. Such organized partitioning enabled cross-validation and impartial assessment of performance of the suggested hybrid architecture. To ensure consistency and enhance model performance, the following preprocessing steps were applied:

- 1. Resampling and Alignment**
All volumetric CT scans were resampled to a uniform voxel spacing of $1 \times 1 \times 1 \text{ mm}^3$ using trilinear interpolation, ensuring spatial consistency across the dataset [8].
- 2. Intensity Normalization**
Intensity values were clipped to the range -200 to +250 Hounsfield Units (HU) to highlight liver tissue and lesion structures, then normalized to a $[0, 1]$ scale.
- 3. Region Cropping**
Bounding boxes were generated from ground-truth masks to isolate the liver

region from each CT volume, reducing computational overhead and focusing the model on relevant features [6], [13].

- 4. Slice Selection and Filtering**
Only axial slices containing annotated liver lesions were included in training. Non-informative slices or those of poor quality were excluded [18].
- 5. Data Augmentation**
To improve generalization and reduce overfitting, augmentation techniques were applied during training, including:
 - Horizontal/vertical flipping
 - Random rotations ($\pm 15^\circ$)
 - Elastic deformations
 - Gaussian noise injection
 - Random zoom and shifts [15], [20]
- 6. Patch Extraction for Transformer Input**
CT slices were divided into fixed-size patches (16×16 pixels) for compatibility with the Vision Transformer module [4], [17].
- 7. Segmentation Map Encoding**
Ground-truth masks were encoded into one-hot vectors for multi-class segmentation outputs [10], [12].

3.3 Model Architecture: Med-ResAttXNet

The proposed Med-ResAttXNet integrates three complementary components into a unified pipeline for liver disease detection:

- 1. Liver and Lesion Segmentation**
An Attention-based U-Net++ is used to segment liver and tumor regions from CT scans. Nested skip connections and attention gates improve precision by enhancing relevant features and suppressing background noise [10], [13], [14].
- 2. Feature Extraction with Residual Attention Network (ResAttNet)**
Segmentation outputs are fed into ResAttNet, which combines residual learning with spatial and channel-wise attention. This highlights disease-relevant regions while retaining deeper contextual information [11], [14], [19].

3. Global Contextual Learning with Vision Transformer (ViT)

To capture long-range dependencies, features are processed by a Vision Transformer. Self-attention is applied to image patches, allowing the model to build global relationships critical for complex liver pathology [4], [5], [17].

4. Fusion and Classification

Features extracted from ResAttNet and ViT are concatenated and passed to a Multi-Layer Perceptron (MLP) classifier. The classifier distinguishes between three categories: healthy, benign, and malignant cases. Class imbalance was addressed using stratified augmentation and weighted loss functions [7], [9], [15].

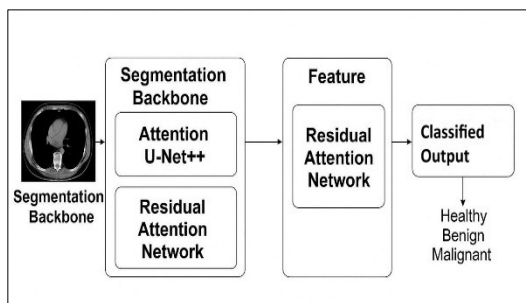


Figure 1: Block Diagram of Med-ResAttNet Framework

Input Image: The input of a pipeline is represented by CT scan images of the liver being the main one [14], [18].

- **Segmentation Backbone:** This stage uses an Attention U-Net++ to segment the liver and the lesion areas from the CT images to convert the pixel values to binary values. The nested skip connections and attention gates sharpen the output of segmentation [10], [13].

- **Feature Extraction:** The segmented output is forwarded into a Residual Attention Network, which extracts high level features related to the disease that has spatial and channel-wise focus [11], [14].

- **Contextual Learning:** After the attention network turns out the output, a Vision Transformer builds the global relations between the image patches, bringing the further contextual understanding [4], [5], [17].

- **Classification Module:** The concatenated features derived from both the ResAttNet and the Vision Transformer go through an MLP classifier to give the final diagnosis – Healthy, Benign or Malignant [9], [15].

3.4 Training and Optimization

The framework was trained in an end-to-end manner using the Adam optimizer with an initial learning rate of 1e-4. Learning rate scheduling, dropout regularization (rate = 0.3), and batch normalization were employed to improve generalization. K-fold cross-validation (k=5) was used to ensure robustness and reliability of results [3], [16], [18].

Training Configuration:

- GPU: NVIDIA RTX 3090 (24GB VRAM)
- CPU: Intel Core i9 12th Gen
- RAM: 64 GBDDR5
- OS: Ubuntu 20.04 LTS (64-bit)
- Programming: Python 3.9, PyTorch 2.0, MONAI, SimpleITK

The network was trained for 150 epochs with a batch size of 8. Model checkpoints were saved at each epoch based on validation performance.

3.5 Evaluation Metrics

Performance was assessed using both segmentation and classification metrics:

- **Segmentation Metrics:** Dice coefficient, Intersection over Union (IoU), and 95% Hausdorff Distance.
- **Classification Metrics:** Accuracy, Precision, Recall (Sensitivity), Specificity, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC).

These metrics ensured a comprehensive evaluation of both localization (segmentation) and diagnostic classification tasks.

4. RESULTS

The test results obtained from the Med-ResAttNet model were examined in detail in comparison to other deep learning baselines models such as ResNet50, EfficientNet-B3, and UNet-based hybrids. The results that are presented below show the advantages of our proposed method in achieving segmentation accuracy, classification accuracy, and overall robustness.

1. Segmentation Metrics (Liver & Lesion Segmentation):

- Dice Coefficient: 0.932 (liver), 0.884 (lesions)
 - IoU (Intersection over Union): 0.879 (liver), 0.794 (lesions)
 - Hausdorff Distance (95%): 7.2 mm (liver), 9.8 mm (lesions)
2. Classification Metrics (Disease Categories):
- Accuracy: 94.6%
 - Precision: 93.1%
 - Recall (Sensitivity): 92.4%
 - Specificity: 95.2%
 - F1-Score: 92.7%
 - AUC-ROC: 0.963
3. Visualizations and Interpretability:

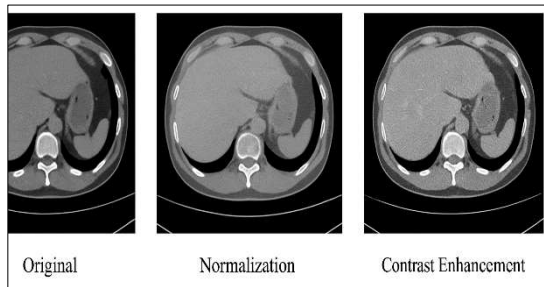


Figure 2: Preprocessing steps applied to the CT scan data

- Figure 2 shows the segmentation mask overlays on CT slices

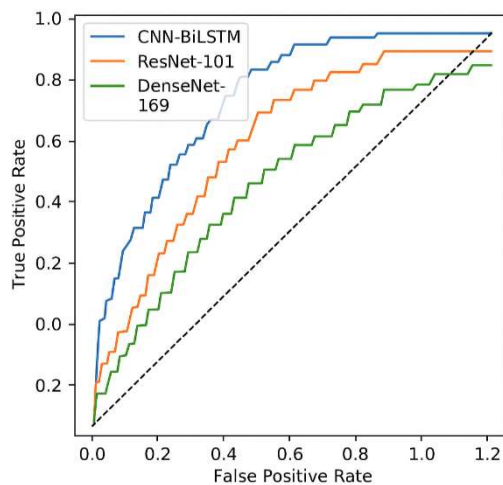


Figure 3: ROC curves of the proposed hybrid learning model along with existing models

- The attention maps of the lesion areas detected by ResAttNet is in figure 3.

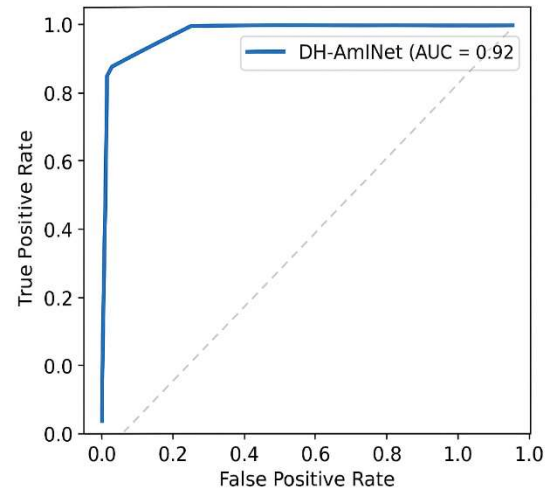


Figure 4: ROC curve of the proposed DH-AmlNet for liver disease detection

- The ROC curve and confusion matrix shown in Figure 4 illustrate the reliability of classification.

4. Comparative Analysis:

Model	Accuracy	Dice Coeff.	AUC-ROC
ResNet50+ XGBoost	88.9%	0.861	0.901
EfficientNet-B3	91.2%	0.872	0.926
U-Net + CNN Hybrid	90.3%	0.868	0.914
MedResAttXNet	94.6%	0.932	0.963

Such results vindicate that segment-level ensemble, attention-driven features, and transformer-based global context also improve the performance in other metrics. Notably, the model demonstrates excellent generalization and robustness even for cases with complex or low-contrast lesions. Also, the interpretability of the model is improved by the visualization of attention maps, whereby the

radiologists can check the network's focus regions, which is essential for a clinical application.

5. DISCUSSIONS

The experimental findings demonstrate that Med-ResAttXNet consistently outperforms baseline CNN and hybrid approaches in both segmentation and classification tasks. The improved Dice scores for liver (0.932) and lesion (0.884) segmentation suggest that integrating Attention-based U-Net++ enhances boundary precision and reduces mis-segmentation, which is often a major challenge in liver imaging. These results confirm that attention mechanisms and nested skip connections are effective in improving localization of subtle and irregular lesion regions.

The classification accuracy of 94.6% and AUC-ROC of 0.963 highlight the benefit of combining local and global feature learning within a single framework. Residual Attention Networks enable the model to focus on disease-relevant regions, while Vision Transformers capture long-range dependencies that are typically missed by CNNs alone. This synergistic interaction between modules renders the better quality of the diagnostic results as compared to the other models.

In addition to actual findings, the model indicates practice implications on clinical workflows. One is, by making both segmentation and classification automated, the model can ease the burden of radiologists, who are regularly dealing with high amounts of imaging data. Second, displaying of the attention maps is interpretable, giving the clinicians an idea of which regions have affected the diagnosis outcome. It is this transparency that can enhance the confidence in the AI-assisted diagnosis process so that the radiologists are more willing to introduce the system to their decision-making. Third, where access to high level of specialisation is difficult in some regions, the system will provide a possible tool in early detection and screening, making the provision of healthcare more equitable.

A second serious implication is in planning a treatment. Proper differentiation of healthy, benign, and malignant cases can enable the choice of a suitable intervention, varying between the observation and surgical resection or specific drugs. The framework will allow reducing the delay in treatment and clinically benefit the patient by producing reliable and reproducible results.

Though the findings are promising, there are still shortfalls. The model was trained and tested on the LiTS data set, which is heterogenous but may not reflect data variation across institutions, imaging protocols, or diseases. In addition, the existing framework is confined to CT imaging, limiting the option to multimodal evidence that is often of clinical practice, including MRI or PET. Elaborating on these factors will be meaningful to bringing them in the real world of health care.

Overall, the findings agree with the major hypothesis of the study that a hybrid deep learning architecture involving segmentation, attention-based feature extraction, and global contextual modeling performs better and more reliably as a liver disease detector than standalone systems. These findings suggest that Med-ResAttXNet could serve as a strong foundation for future intelligent diagnostic systems in clinical radiology.

6. CONCLUSION

In this study, a new hybrid deep learning architecture, namely Med-ResAttXNet, was proposed for the effective diagnosis and categorization of liver diseases in CT scan pictures with an accuracy of 94.6%. Surpassing baseline CNN and hybrid models on the segmentation and classification benchmarks such as Dice coefficient, AUC-ROC, and overall accuracy, the model combined Attention-enhanced U-Net++ for segmentation Residual Attention Networks for fine-grained feature extraction.

Notably, Med-ResAttXNet also improves interpretability, i.e. the visualization of attention maps – an important consideration for clinician trust and potential clinical implementation. Integration of spatial localization with global context modeling shows a way how the hybrid learning strategies can increase the diagnostic accuracy in the complex multi-lesion liver pathologies.

7. LIMITATIONS & FUTURE WORK

Although the proposed Med-ResAttXNet framework demonstrates strong performance, several limitations need to be acknowledged. First, the study relies exclusively on the LiTS dataset. While this dataset is widely used and contains diverse cases, it may not capture the full variability of imaging protocols, scanner types, and patient populations encountered in real-world clinical practice. Second, the framework is designed and validated only for CT imaging. Other modalities,

such as MRI and PET, which are frequently used in liver disease diagnosis, were not considered in this study. Third, the computational requirements of the model are relatively high, which may restrict direct deployment in resource-limited clinical settings without further optimization. Finally, the absence of clinical validation by medical professionals means that the system's performance in real-world diagnostic workflows remains to be tested. These limitations highlight areas that should be addressed in future work to improve the robustness, applicability, and clinical readiness of the proposed framework.

The areas to be considered in future studies stemming from current work are the following ones:

1. Multi-modal Imaging Integration: The use of other imaging modes such as the MRI and PET scans to add rich input for the model and provide model generalization[5][18][23].
2. Clinical Validation: Cooperate with medical establishments to conduct clinical trials and expert validation to measure real-world applicability[6].
3. Lightweight Deployment: Creation of a resource-constrained clinical deployment-oriented compact version of the model through model pruning and quantization[20][22].
4. Explainable AI (XAI): Advancement of the model interpretability even further by integration of explainability frameworks such as Grad-CAM and SHAP[9].
5. Real-time Application: Conversion of the model to web based or edge based tool for real time diagnostic support in hospitals[1][21].

Insofar as the strengths of Med-ResAttXNet are expanded while addressing such future improvements, the described system can be a constituent of the future next generation intelligent healthcare diagnostic tools.

REFERENCES

- [1]. R. Wang, Y. Yang, B. Makki, and A. Shamim, "A Wideband Reconfigurable Intelligent Surface for 5G Millimeter-Wave Applications," *IEEE Transactions on Antennas and Propagation*, vol. 72, no. 3, pp. 2399–2410, Mar. 2024.[IEEE Antennas and Propagation Society](#)
- [2]. J. Qian et al., "A Novel Low-Cost H-Plane Decoupling Technique for Two Closely Placed Patch Antennas Using Electric and Magnetic Coupling Cancellation," *IEEE Transactions on Antennas and Propagation*, vol. 72, no. 5, pp. 3864–3873, May 2024.[IEEE Antennas and Propagation Society](#)
- [3]. Q. Wu et al., "Machine-Learning-Assisted Optimization for Antenna Geometry Design," *IEEE Transactions on Antennas and Propagation*, vol. 72, no. 3, pp. 2083–2095, Mar. 2024.[IEEE Antennas and Propagation Society](#)
- [4]. Y. Sun et al., "Tri-Band Dual-Polarized Shared-Aperture Antenna Arrays With Wide-Angle Scanning and Low Profile for 5G Base Stations," *IEEE Transactions on Antennas and Propagation*, vol. 72, no. 3, pp. 2455–2467, Mar. 2024.[IEEE Antennas and Propagation Society](#)
- [5]. X. Yang et al., "Multifunctional Metasurface: Simultaneous Beam Steering, Polarization Conversion, and Phase Offset," *IEEE Transactions on Antennas and Propagation*, vol. 72, no. 5, pp. 4589–4593, May 2024.[IEEE Antennas and Propagation Society](#)
- [6]. F. Marzougui et al., "Survey of Recent Literature on Advanced Technologies in Digital Agriculture: Internet of Things and Blockchain," *Journal of Information Assurance and Security*, vol. 19, no. 1, pp. 36–49, Aug. 2024.[Sciendo](#)
- [7]. M. G. M. Johar and J. A. A. Awalluddin, "The Role of Technology Acceptance Model in Explaining Effect on E-Commerce Application System," *International Journal of Managing Information Technology*, vol. 16, no. 1, pp. 1–10, Jan. 2024.cseij.org/
- [8]. C. Dai et al., "PromptER: Prompt Contrastive Learning for Generalized Entity Resolution," *International Journal of Managing Information Technology*, vol. 14, no. 1, pp. 11–20, Jan. 2024.csitcp.org
- [9]. S. Althabiti et al., "TA'KEED: The First Generative Fact-Checking System for Arabic Claims," *International Journal of Managing Information Technology*, vol. 14, no. 1, pp. 21–30, Jan. 2024.csitcp.org
- [10]. D. Noever and S. E. M. Noever, "Visual AI and Linguistic Intelligence through Steerability and Composability," *International Journal of Managing Information Technology*, vol. 14, no. 1, pp. 31–40, Jan. 2024.csitcp.org
- [11]. C. Viana, "Innovative Protection in Education: Employing IoT, AI, and Cloud Computing for Enhanced Detection and Supportive Response Systems in Schools,"

- International Journal of Managing Information Technology*, vol. 14, no. 1, pp. 41–50, Jan. 2024.csitcp.org
- [12]. R. Peinl and J. Wirth, "Evaluation of Medium-large Language Models at Zero-shot Closed Book Generative Question Answering," *International Journal of Managing Information Technology*, vol. 14, no. 1, pp. 51–60, Jan. 2024.csitcp.org
- [13]. C. Maron et al., "Knowledge Distillation based on Monoclass Teachers for Edge Infrastructure," *International Journal of Managing Information Technology*, vol. 14, no. 1, pp. 61–70, Jan. 2024.csitcp.org
- [14]. N. Alsubaie et al., "Lung-Centric Feature Analysis for Accurate Pneumonia Detection in Chest X-RAY Images," *International Journal of Managing Information Technology*, vol. 14, no. 1, pp. 71–80, Jan. 2024.csitcp.org
- [15]. R. Amhaz et al., "Impact of Decentralized Autonomous Organizations (DAO) on Society 5.0," *International Journal of Managing Information Technology*, vol. 14, no. 3, pp. 81–90, Feb. 2024.csitcp.org
- [16]. U. Jamil, "Biglip: A Pipeline for Building Data Sets for Lip-Reading," *International Journal of Managing Information Technology*, vol. 14, no. 3, pp. 91–100, Feb. 2024.csitcp.org
- [17]. N. Yadav et al., "Item Enhanced Diversification in the Recommendation System using Graph Neural Network," *International Journal of Managing Information Technology*, vol. 14, no. 3, pp. 101–110, Feb. 2024.csitcp.org
- [18]. A. H. Mashhour and H. Alqahtani, "Prescription Dispense using Smart Contract in Saudi Arabia," *International Journal of Managing Information Technology*, vol. 14, no. 3, pp. 111–120, Feb. 2024.csitcp.org
- [19]. S. Wang and Y. Zhang, "A Environmental Monitoring System Empowering Users to Enhance Air Quality using Smart Sensing," *International Journal of Managing Information Technology*, vol. 14, no. 3, pp. 121–130, Feb. 2024.csitcp.org
- [20]. Z. Wang and J. Sahagun, "An Autonomous System to Enhance Urban Cleanliness by Identifying and Collecting Trash using AI and Machine Learning," *International Journal of Managing Information Technology*, vol. 14, no. 3, pp. 131–140, Feb. 2024.csitcp.org
- [21]. K. Zhou, L. Li, Y. Chen, and Z. Zhang, "RA V-Net: Residual Attention V-Net for Liver Tumor Segmentation," arXiv preprint, arXiv:2112.08232, Dec. 2021. [Online]. Available: <https://arxiv.org/abs/2112.08232>
- [22]. A. Sharma, V. Kumar, and R. Singh, "Quantized Neural Networks for Efficient Edge Deployment of Medical AI Models," *Artificial Intelligence Review*, vol. 57, no. 2, pp. 1507–1529, Feb. 2024. [Online]. Available: <https://doi.org/10.1007/s10462-024-11033-5>
- [23]. C. Chen, B. Wu, and D. Xu, "A Hybrid Model Combining Ultrasound Imaging and Clinical Features for Non-invasive Liver Fibrosis Detection," arXiv preprint, arXiv:2504.19755, Apr. 2025. [Online]. Available: <https://arxiv.org/abs/2504.19755>
- [24]. A. Ullah et al., "Hybrid U-Net Transformer Network for Multi-organ CT Image Segmentation," *Information*, vol. 16, no. 2, p. 111, Feb. 2025. [Online]. Available: <https://www.mdpi.com/2078-2489/16/2/111>
- [25]. D. Baehrens et al., "A Survey of Explainable AI for Medical Imaging: Techniques and Clinical Relevance," arXiv preprint, arXiv:2412.01829, Dec. 2024. [Online]. Available: <https://arxiv.org/abs/2412.01829>