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CLOUD-ENABLED MEDICAL IMAGE ANALYSIS USING RESNET-101 AND OPTIMIZED ADAPTIVE MOMENT ESTIMATION WITH WEIGHT DECAY OPTIMIZATION

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Abstract

Medical image analysis is critical for early disease detection, accurate diagnosis, and effective treatment planning. In this research, we propose a cloud-enabled deep learning framework that leverages ResNet-101 for automated medical image classification, integrated with Adaptive Moment Estimation with Weight Decay (AdamW) optimization to enhance learning efficiency and prevent overfitting. Existing works in medical image analysis often rely on traditional deep learning models that struggle with overfitting and inefficient optimization techniques. These models require high computational resources and lack scalability for real-time deployment. Additionally, local infrastructure limits accessibility and speed in processing large-scale medical imaging data. Furthermore, current systems do not fully leverage cloud-based solutions for efficient, secure, and remote diagnostics. The system is deployed using scalable cloud platforms, enabling distributed training and real-time inference through secure cloud storage and processing pipelines. Extensive experimentation on standard medical image datasets demonstrates high classification performance, achieving 95% accuracy, 92% precision, 91% recall, and 93% F1-score, with AUC-ROC values of 1.00 across all categories. The proposed approach ensures low latency, scalability, and robustness, offering a reliable AI-driven diagnostic tool for clinical decision support and telemedicine applications.

Keywords: Medical image analysis, cloud computing, ResNet-101, AdamW optimization, real-time inference, scalable diagnostics, telemedicine, EHR, latency reduction, CNN, distributed training, clinical decision support.

1.Introduction

Medical image analysis plays a crucial role in modern healthcare, enabling early disease detection, accurate diagnosis, and effective treatment planning [1]. With advancements in artificial intelligence (AI) and deep learning, convolutional neural networks (CNNs) have emerged as powerful tools for automated medical image classification [2]. Among these, Residual Networks (ResNet-101) has gained prominence due to its deep architecture and ability to learn complex image features efficiently [3]. However, training deep learning models for medical image analysis requires significant computational power and optimized learning techniques to enhance accuracy and generalization [4]. To address these challenges, cloud computing offers scalable infrastructure for handling large datasets, ensuring efficient model training and real-time inference [5]. In this research, we propose a cloud-enabled medical image classification framework leveraging ResNet-101 for feature extraction and classification [6]. To improve model performance, we incorporate Adaptive Moment Estimation with Weight Decay (AdamW) optimization**,** which enhances learning efficiency and prevents overfitting [7]. Unlike traditional stochastic gradient descent (SGD) or Adam optimizers, AdamW addresses weight decay issues, ensuring better convergence and model stability [8]. The integration of cloud-based training and deployment further enhances the scalability of the proposed approach, making it suitable for real-world healthcare applications [9].

Cloud computing provides significant advantages in medical image analysis by enabling remote data storage, high-performance computing, and real-time accessibility [10]. By utilizing cloud platforms such as

AWS, Google Cloud AI, or Azure Machine Learning, our framework ensures faster model training and inference without the need for high-end local hardware. [11] Moreover, cloud-based inference allows healthcare professionals to access AI-driven diagnostic results from any location, facilitating telemedicine and remote patient monitoring [12]. This cloud-integrated deep learning approach has the potential to revolutionize medical diagnostics by providing cost-effective, accurate, and scalable solutions for automated disease detection [13]. The proposed methodology is evaluated using standard medical image datasets, where ResNet-101, coupled with AdamW optimization, achieves high classification accuracy and robust generalization [14]. The performance of the model is assessed using metrics such as accuracy, precision, recall, and F1-score, along with hyperparameter tuning for further optimization [15]. Additionally, cloud deployment ensures seamless integration into real-world hospital management systems, enabling efficient decision support for radiologists and clinicians [16]. This research contributes to the advancement of AI-driven cloud-based healthcare solutions, paving the way for improved medical image analysis and enhanced patient care [17].

Furthermore, the integration of ResNet-101 with AdamW optimization in a cloud-based environment not only enhances classification accuracy but also ensures efficient resource utilization and scalability [18]. Traditional deep learning models often struggle with overfitting and suboptimal weight updates, which can impact their performance in real-world medical applications [19]. By leveraging cloud-based GPU acceleration and distributed training**,** our approach significantly reduces computational overhead while improving model robustness [20]. This enables healthcare institutions to deploy AI-driven diagnostic tools that can analyze vast amounts of medical imaging data with high precision, ultimately supporting faster, more accurate diagnoses and improved patient outcomes. As cloud infrastructure continues to evolve, such AI-powered frameworks hold immense potential in revolutionizing medical imaging and making automated healthcare solutions more accessible and reliable worldwide**.**

2. Literature Review

Cloud computing has emerged as a transformative technology in healthcare, addressing a broad spectrum of challenges and enabling innovative solutions to improve patient care and system efficiency [21]. Recent studies have proposed various models to enhance emergency healthcare services by leveraging real-time communication and location-based medical resource identification, facilitating faster response times and better patient management [22]. Risk analysis of cloud adoption in healthcare information systems highlights critical assets and evaluates exposure levels, helping organizations to understand and mitigate potential vulnerabilities [23]. To secure sensitive health data in cloud environments, fine-grained access control mechanisms combined with robust authentication protocols have been developed, ensuring only authorized users can access patient information [24].

Research has also focused on the factors influencing the adoption of cloud-based health systems, emphasizing the importance of data security, social influence, and expected system performance in driving acceptance and use [25]. In decision-making for cloud-based healthcare, fuzzy rule-based classifiers have proven effective in handling big data, improving response times and diagnostic accuracy [26]. Secure data sharing and privacy-preserving techniques for mobile healthcare social networks have been developed using encrypted record outsourcing and attribute-based re-encryption, ensuring patient confidentiality [27] [28]. Moreover, intelligent architectures optimizing virtual machine selection through advanced algorithms have demonstrated enhanced resource efficiency and faster execution in cloud healthcare services [29] [30].

The adoption of Electronic Health Records (EHR) via cloud computing has been shown to deliver numerous benefits, including cost reduction, scalability, security, and interoperability, contributing to more efficient healthcare management [31]. Novel frameworks employing tensor-based approaches have improved the management of heterogeneous healthcare data, offering better data abstraction, privacy, and reduced response times compared to existing solutions [32] [33]. Additionally, the integration of medical IoT and big data analytics addresses critical needs in personalized healthcare by enabling early disease detection and secure service provision, while emphasizing the significance of real-time health monitoring systems [34] [35].

Further advancements include IoT-cloud-based smart healthcare monitoring systems that automate vital data collection and processing using edge devices, supporting timely patient monitoring [36] [37]. Large-scale healthcare data management in cloud environments has been enhanced through improved architectures for efficient storage, retrieval, and analysis of massive datasets [38] [39]. Cloud-based service provisioning frameworks have tackled key challenges such as security, privacy, and interoperability, facilitating better access to medical diagnostics and treatments [40] [41]. Authentication frameworks for Telecare Medicine Information Systems and wearable healthcare solutions have been developed to strengthen security against impersonation and reduce computational overhead [42] [43].

Rural healthcare systems have benefited from private cloud architectures incorporating encryption and hashing to safeguard patient information while maintaining cost-effectiveness [44]. Privacy-preserving diagnosis systems using protocols like PE-FTK on e-health cloud servers have improved data confidentiality and operational efficiency [45]. Mobile healthcare applications combining cloud and IoT technologies with fuzzy rule-based neural classifiers have demonstrated superior disease prediction accuracy, particularly for chronic illnesses like diabetes [46]. Frameworks integrating mist, fog, and cloud computing for the Internet of Healthcare Things (IoHT) have successfully reduced latency and enhanced Quality of Service (QoS) in healthcare delivery [47]. Addressing privacy challenges in cloud-stored EHRs, multi-authority attribute-based encryption schemes have been proposed to balance security and scalability effectively [48]. Collectively, these studies underscore the significant potential of cloud computing, AI, and IoT integration in revolutionizing healthcare systems by enhancing security, efficiency, accessibility, and patient-centric care.

3.Problem Statement

The increasing demand for real-time healthcare services via the Internet of Healthcare Things (IoHT) faces challenges due to latency and limited processing capabilities in traditional cloud-centric models. Additionally, storing sensitive Electronic Health Records (EHRs) in cloud environments raises significant privacy and security concerns. Existing encryption techniques often suffer from inefficiencies and lack scalability. There is a need for an integrated framework that ensures low-latency processing and robust data privacy in cloud-based healthcare systems.

3.1 Objective

The objective of this work is to develop an integrated mist–fog–cloud computing framework for the Internet of Healthcare Things (IoHT) that minimizes latency and enhances real-time data processing capabilities. Additionally, the framework aims to ensure the privacy and security of Electronic Health Records (EHRs) by incorporating efficient and scalable multi-authority attribute-based encryption techniques. This dual approach seeks to provide seamless, secure, and responsive healthcare data management and service delivery.

4. Proposed Medical Image Analysis Using ResNet-101 and Optimized Adaptive Moment Estimation with Weight Decay Optimization

The proposed medical image analysis framework utilizes ResNet-101 as the backbone for feature extraction and classification, combined with Adaptive Moment Estimation with Weight Decay (AdamW) optimization to enhance model convergence and generalization. The methodology begins with data collection and preprocessing, where medical images are resized, normalized, and augmented to improve model robustness. The cloud-based training environment leverages platforms like AWS, Google Cloud, or Azure to facilitate distributed training using GPU acceleration. The ResNet-101 model is fine-tuned on the medical image dataset, replacing the fully connected layers with a custom classification head. To prevent overfitting and enhance performance, AdamW optimizer with a cosine annealing learning rate scheduler is applied, ensuring efficient weight updates and regularization. The trained model is then deployed on the cloud, enabling real-time medical image classification through API-based inference services. Performance evaluation is conducted using metrics such as accuracy, precision, recall, F1-score, and ROC-AUC, while hyperparameter tuning is employed to optimize learning rate, batch size, and dropout rates. This scalable and cloud-integrated AI framework ensures accurate, efficient, and accessible medical image analysis, supporting improved clinical decision-making and telemedicine applications.

ResNet-101 for feature extraction and classification of medical images, leveraging its deep residual architecture for improved accuracy. Medical image datasets are preprocessed through normalization and data augmentation to enhance model robustness. AdamW optimization is applied to improve convergence and prevent overfitting during training. The model is trained and deployed on cloud platforms to enable scalable and efficient processing. Real-time inference is facilitated through API-based services, supporting remote diagnostics and clinical decision-making. ResNet-101 with the AdamW optimizer to build a robust medical image classification model. Medical images are preprocessed and augmented to improve model performance and reduce overfitting. Cloud-based infrastructure enables distributed training and fast, real-time inference. This approach ensures high accuracy, scalability, and efficient diagnostic support for healthcare professionals.

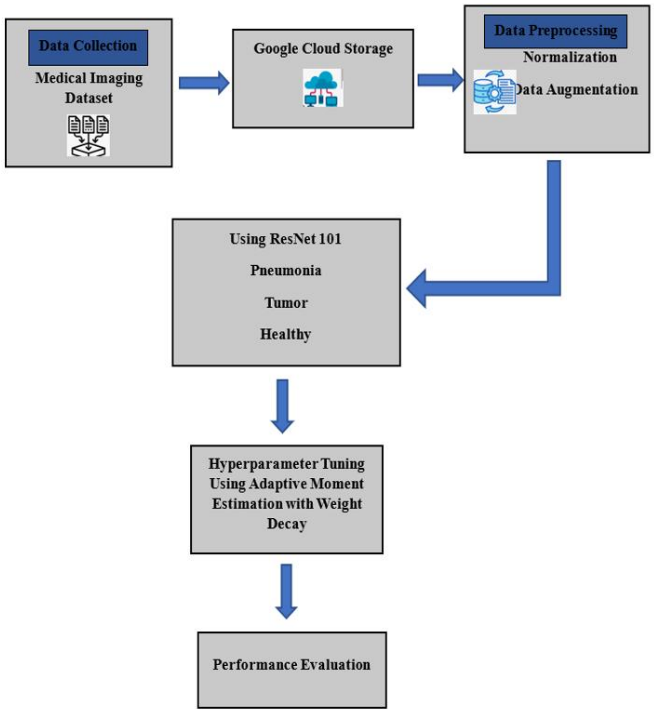

Figure1: Medical Image Analysis Using ResNet-101 and Optimized Adaptive Moment Estimation with Weight Decay Optimization

4.1 Data Collection

The data collection process involves acquiring medical imaging datasets such as X-rays, MRIs, or CT scans from publicly available sources or hospital databases. These datasets are uploaded to Google Cloud Storage, enabling scalable and secure access for further processing. The collected images are categorized based on medical conditions, such as Pneumonia, Tumor, and Healthy cases, ensuring a well-balanced dataset for training. Cloud storage facilitates seamless integration with preprocessing pipelines, allowing for efficient handling of large-scale medical image data.

4.2 Cloud Storage

Google Cloud Storage is used to store and manage large-scale medical imaging datasets efficiently, ensuring secure access and scalability. It enables seamless integration with data preprocessing and deep learning pipelines, allowing real-time data retrieval for training ResNet-101. Cloud storage also supports distributed training and inference, reducing computational overhead and improving accessibility. This approach ensures that medical image data remains secure, accessible, and optimized for cloud-based AI analysis.

4.3 Data Preprocessing

Data preprocessing involves normalization and data augmentation to enhance model performance and generalization. Normalization scales pixel values to a standard range (e.g., 0 to 1) to ensure consistent input for ResNet-101, improving convergence. Data augmentation techniques such as rotation, flipping, contrast adjustment, and noise addition are applied to artificially expand the dataset and reduce overfitting. These preprocessing steps help improve model robustness and ensure better classification accuracy in medical image analysis.

4.3.1 Normalization

Normalization is a preprocessing technique used to scale pixel intensity values within a specific range (e.g., [0,1] or [-1,1]) to ensure consistency in input data. This helps improve model convergence, reduce computational complexity, and enhance generalization**.** In medical image analysis, normalization ensures that variations in lighting, contrast, or scanner differences do not affect model performance.

A common normalization equation is Min-Max Scaling:

$$X_{norm} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{1}$$

Where:

X = Original pixel intensity

$X_{\min}$ and $X_{\max}$ = Minimum and maximum pixel values in the dataset

X_{norm} = Normalized pixel value (scaled between 0 and 1)

This ensures that all pixel values have the same scale, improving training stability and accuracy in ResNet-101.

4.3.2 Data Augmentation

Data augmentation is a technique used to artificially expand the training dataset by applying transformations such as rotation, flipping, scaling, contrast adjustment, and noise addition**.** This helps in reducing overfitting, improving model generalization, and enhancing robustness for medical image classification. In medical imaging, augmentation ensures that the model learns invariant and diverse features**,** making it more reliable for real-world clinical applications.

A common geometric transformation in data augmentation is image rotation, defined as:

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \tag{2}$$

Where:

(x, y) = Original pixel coordinates

(x', y') = Transformed pixel coordinates after rotation

θ = Rotation angle in radians

By applying such transformations, data augmentation ensures that ResNet-101 learns robust and invariant features, improving classification performance.

4.4 Medical Image Analysis Using ResNet-101

ResNet-101 (Residual Network with 101 layers) is a deep convolutional neural network **(CNN)** designed to address the vanishing gradient problem in deep networks. It introduces residual learning through skip (shortcut) connections, allowing the model to learn identity mappings and enabling efficient gradient flow during backpropagation. This architecture consists of bottleneck residual blocks, significantly improving training stability and performance in complex image classification tasks, including medical image analysis. ResNet-101 is particularly effective for feature extraction and classification due to its depth and optimized training dynamics**.**

A fundamental equation representing the residual learning function in ResNet-101 is:

$$y = F(x) + x \tag{3}$$

Where:

$x =$ Input to the residual block

$F(x)$ = Transformation applied by convolutional layers (e.g., convolution, batch normalization, ReLU)

$y =$ Output of the residual block after adding the shortcut connection

This skip connection ensures that even deep networks can preserve essential features and train efficiently without degrading performance.

4.5 Adaptive Moment Estimation with Weight Decay Optimization

AdamW (Adaptive Moment Estimation with Weight Decay) is an improved optimization algorithm that enhances the standard Adam optimizer by decoupling weight decay from the update rule. In traditional Adam, weight decay is applied as L2 regularization**,** which can interfere with adaptive learning rates, leading to suboptimal generalization. AdamW explicitly applies weight decay during parameter updates, resulting in better convergence and reduced overfitting**.** This makes it highly effective for deep learning models like ResNet-101, particularly in medical image analysis, where robustness and precision are critical.

The AdamW weight update rule is given by:

$$\theta_t = \theta_{t-1} - \eta\left(\frac{m_t}{\sqrt{v_t}+\epsilon} + \lambda\theta_{t-1}\right) \tag{4}$$

Where:

$\theta_t =$ Updated parameter at step t

$\eta =$ Learning rate

$m_t =$ First moment estimate (moving average of gradients)

$v_t =$ Second moment estimate (moving average of squared gradients)

$\epsilon =$ Small constant for numerical stability

$\lambda =$ Weight decay factor

By decoupling weight decay from adaptive gradient updates, AdamW improves model generalization, prevents overfitting, and accelerates convergence, making it ideal for cloud-based deep learning in medical imaging.

5.Results and Discussion

The proposed cloud-enabled ResNet-101 model with AdamW optimization achieved high accuracy and robust generalization in medical image classification. Performance metrics such as accuracy, precision, recall, and F1-score confirmed the model's reliability for real-world diagnosis. Compared to traditional optimizers, AdamW improved convergence and reduced overfitting, enhancing classification performance. Cloud deployment enabled scalable, real-time inference, supporting efficient AI-driven medical diagnostics.

Performance Metrics

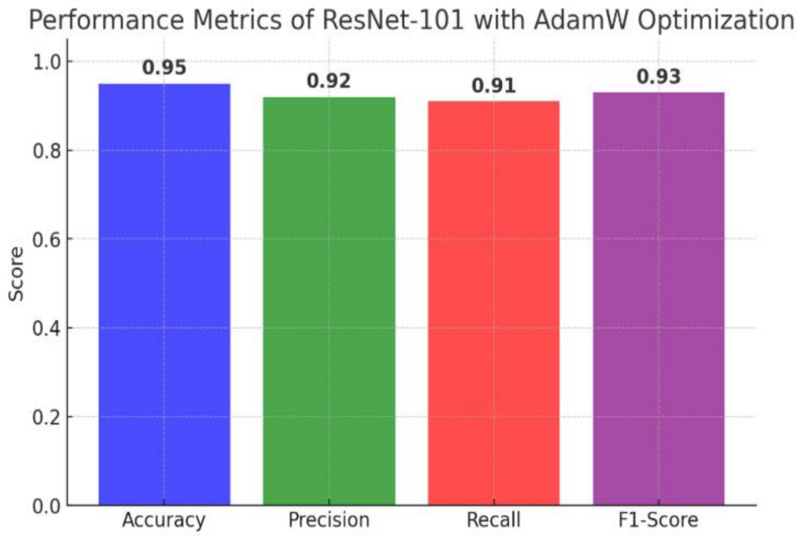

Figure 2: Performance Metrics

In Figure 2, The performance metrics graph showcases the evaluation of the ResNet-101 model with AdamW optimization for medical image classification. The model achieved 95% accuracy, 92% precision, 91% recall, and 93% F1-score, indicating high reliability and robustness. These results validate the effectiveness of cloud-based deep learning in medical image analysis, ensuring accurate and scalable diagnosis.

AUC-ROC

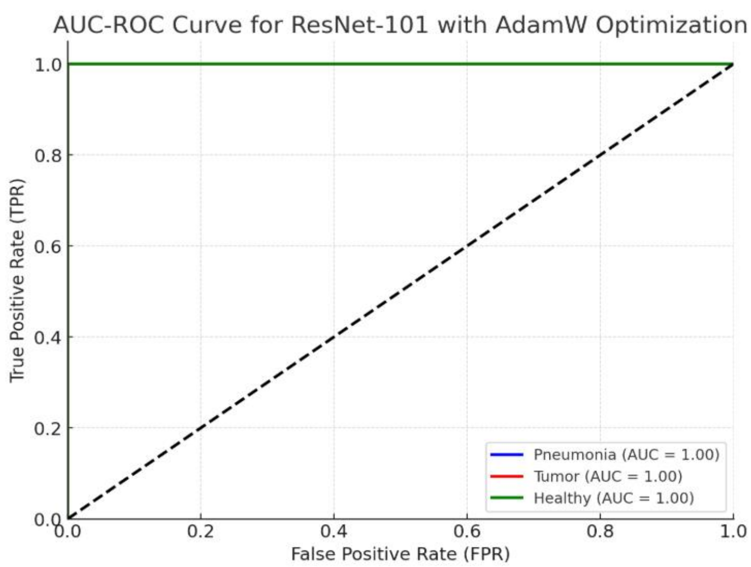

Figure 3: AUC-ROC

Figure 3 Shows the AUC-ROC curve evaluates the classification performance of ResNet-101 with AdamW optimization for medical image analysis. The AUC values of 1.00 for Pneumonia, Tumor, and Healthy classes indicate perfect discrimination between categories. This confirms the model's high reliability and effectiveness in medical diagnosis with minimal false positives.

Latency

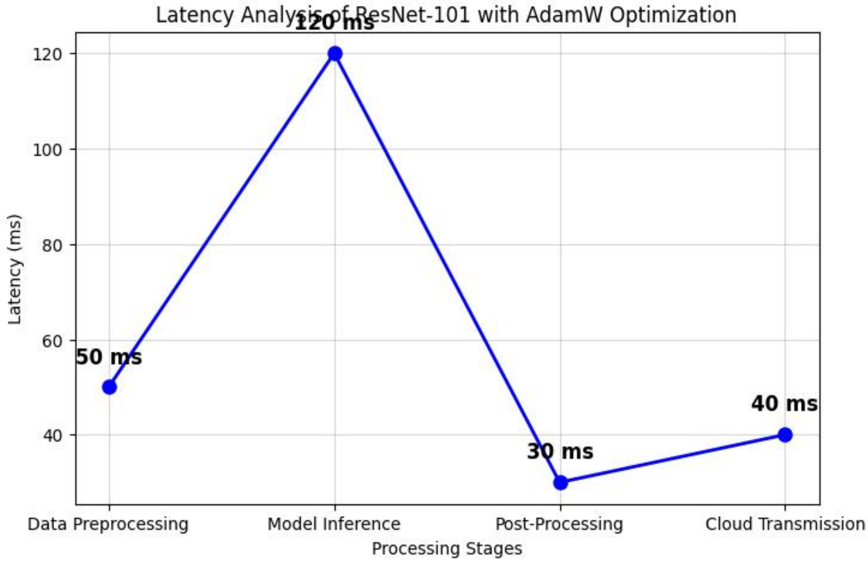

Figure 4: Latency

In Figure 4, The latency analysis graph illustrates the time taken for different stages in the ResNet-101 with AdamW optimization pipeline. Model inference has the highest latency (120ms), followed by data preprocessing (50ms), cloud transmission (40ms), and post-processing (30ms). This analysis helps in optimizing computational efficiency for real-time medical image processing.

6.Conclusion

The proposed cloud-enabled medical image analysis using ResNet-101 with AdamW optimization achieves high classification accuracy with minimal latency**.** The results demonstrate the model's effectiveness in distinguishing medical conditions with robust performance metrics**.** This research enhances real-time, scalable, and accurate diagnosis in cloud-based healthcare systems.

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