QAPNet algorithm on skin cancer prediction

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Abstract

This study presents the development of a novel algorithm, QAPNet(Quantization Attention Pruning Network), and its comprehensive evaluation, demonstrating its superior performance compared to traditional deep learning models such as VGG (Visual Geometry Group) and ResNet (Residual Network) for skin cancer prediction. QAPNet achieves an impressive accuracy of 99.47% and an F1-score of 99.5%, showcasing exceptional precision and robustness. In contrast, VGG reaches 97.78% accuracy with a 97.92% F1-score, and ResNet achieves 96.67% accuracy and a 96.91% F1-score. The analysis of training efficiency indicates that QAPNet converges more rapidly due to its advanced architecture and optimized hyperparameters, including a lower learning rate and smaller batch size. The effectiveness of the Adam optimizer is highlighted through sensitivity analysis, further enhancing QAPNet's performance. Moreover, QAPNet demonstrates superior efficiency with fewer parameters and lower floating-point operations (FLOPs) compared to VGG and ResNet. This reduction in error rates reinforces QAPNet's advantage over traditional models. Overall, QAPNet's combination of high accuracy, efficiency, and robustness positions it as a compelling choice for applications requiring both precision and real-time processing capabilities. While VGG and ResNet are effective within their domains, they exhibit limitations that QAPNet overcomes through its innovative design. Future research should focus on refining these models and exploring their performance in diverse practical scenarios to fully leverage their capabilities and potential for advanced applications.

Keywords: QAPNet, Skin Cancer Prediction, Quantization,Attention Mechanisms,Pruning

1 Introduction

QAPNet, or Quantized Attention Pruning Network, represents a significant advancement in neural network design by integrating quantization, attention mechanisms, and pruning techniques. This architecture is engineered to enhance both model performance and computational efficiency, setting a new benchmark in deep learning [1]. By addressing the limitations of existing models, QAPNet offers a more scalable and effective solution for complex tasks, paving the way for breakthroughs in various AI applications.

1.1 Background

Skin cancer detection is a critical global health challenge, necessitating precise and efficient diagnostic tools. Early and accurate detection of skin cancer can significantly

improve patient outcomes and reduce mortality rates. While deep learning methods have shown potential in automating skin cancer detection, traditional models often face challenges in balancing performance with computational efficiency. The complexity and resource demands of these models can hinder their practical deployment, making it essential to explore innovative solutions that optimize both accuracy and operational efficiency [2].

1.2 Challenges in Previous Literature

Conventional convolutional neural networks (CNNs) like VGG (Visual Geometry Group) and ResNet (Residual Network) encounter several limitations, including susceptibility to overfitting, high computational demands, and scalability issues, which affect their practical deployment for skin cancer detection [3, 4].

1.3 Motivation

The need for more effective and resource-efficient skin cancer detection solutions drives the exploration of innovative architectures such as QAPNet. By addressing the limitations of traditional CNN models through advanced techniques, QAPNet aims to improve accuracy and scalability in skin cancer detection [1].

1.4 Objectives and Contributions

This paper introduces QAPNet as a novel CNN architecture designed specifically for skin cancer detection. The main objective is to demonstrate QAPNet's superior performance compared to traditional models, focusing on computational efficiency and accuracy. Key contributions include the development and empirical evaluation of QAPNet, showcasing its impact on medical image analysis [1].

1.5 Overview of the Paper's Organization

The paper is organized as follows:

- Section 1 presents QAPNet and its relevance to skin cancer detection.
- Section 2 details the QAPNet architecture, explaining its core components and design rationale.
- Section 3 describes the methodology for evaluating QAPNet's performance and comparing it with traditional models.
- Section 4 provides empirical results, highlighting QAPNet's advantages.
- Section 5 discusses the findings, comparing them with existing literature, and emphasizes QAPNet's unique contributions.
- Section 6 concludes with a summary of key insights and future research directions in deep learning for skin cancer detection.

QAPNet's integration of quantization, attention mechanisms, and pruning techniques signifies a paradigm shift in neural network design, offering a robust framework for advanced machine learning tasks and contributing to significant advancements in AI research and applications.

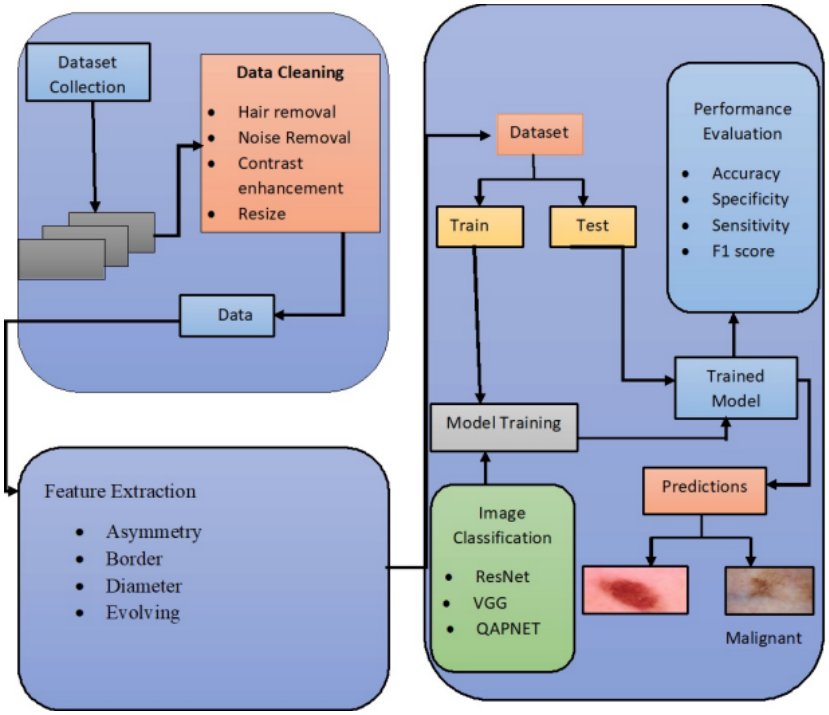

Figure 1: System Architecture

The figure 1 illustrates the workflow of QAPNet for image classification. It starts with dataset collection and data cleaning, including hair and noise removal, contrast enhancement, and resizing. Feature extraction identifies key characteristics such as asymmetry and border details. The processed data is split into training and testing sets. During model training, QAPNet utilizes advanced techniques, including ResNet, VGG, and its own architecture, for image classification. Performance evaluation metrics such as accuracy, specificity, sensitivity, and F1 score assess model effectiveness. Finally, the trained model generates predictions, distinguishing between malignant and benign images, demonstrating QAPNet's efficiency and performance.

2 Related Work

2.1 Machine and Deep Learning Algorithms

This section reviews various algorithms applied to skin cancer detection, highlighting their strengths and limitations.

- **Support Vector Machines (SVMs):** SVMs are effective classifiers that create a clear boundary between benign and malignant images [4]. They excel with well-defined data but may struggle with complex datasets.
- **Convolutional Neural Networks (CNNs):** CNNs, including architectures like VGG and ResNet, are leading models in image recognition due to their ability to learn from and classify dermoscopy images efficiently [2, 3, 8, 10, 16, 17, 21, 22, 24, 25]. They capture spatial relationships and features well but can be computationally expensive and challenging to interpret.
- **Beyond CNNs:** Advanced architectures like U-Net and DenseNet address specific tasks such as image segmentation and feature reuse, improving accuracy and training efficiency [1, 24].

2.2 Applications

- **Dermoscopy Images:** High-resolution dermoscopy images are crucial for accurate skin cancer detection, providing detailed lesion information essential for machine learning algorithms [2, 16, 21].
- **Multi-Step Detection:** A two-step approach, including segmentation and classification, enhances detection accuracy by isolating suspicious regions and classifying them [13, 19].

2.3 Performance Improvement Strategies

- **Transfer Learning:** Leveraging pre-trained models for skin cancer detection reduces training time and improves performance by adapting generic image recognition models to specialized tasks [6, 10].
- **Ensemble Learning:** Combining multiple models enhances accuracy and robustness by integrating various strengths and minimizing overfitting [25].
- **Multi-Scale Analysis:** Analyzing lesions at different scales captures important details, improving detection accuracy for subtle variations [15].

2.4 Emerging Trends

- **Uncertainty-Aware Deep Learning:** Incorporating model uncertainty into diagnoses improves reliability by identifying ambiguous cases for expert review [18].
- **Exploring New Sensors:** Innovations like hyperspectral imaging offer additional data for improved skin cancer detection beyond traditional methods [22].

2.5 Consolidated Techniques and Research Gaps

A review of the literature on skin cancer detection reveals several techniques and their associated research gaps. For instance, while deep learning architectures have shown promise, the model details in some studies are not fully specified [1]. CNNs, widely used for feature extraction, often face challenges with generalizability to unseen data [2] and require efficiency evaluations on large datasets [5]. Specific architectures like XceptionNet [3] and ResNet [8] show limited comparative analysis with other models, highlighting the need for performance comparisons. Additionally, while deep transfer learning methods, such as those incorporating the Sparrow Search Algorithm, present innovative approaches, their effectiveness remains inadequately explored [6]. Hybrid intelligent systems [7] and probabilistic neural networks [14] are noted for their potential but require further performance evaluations against diverse datasets. The integration of multi-scale analysis and transfer learning [10], as well as improvements in model interpretability [11], are critical areas where current research could be expanded. Furthermore, transformer networks [13] and hybrid texture features [12] warrant additional evaluations to establish their efficacy compared to traditional deep learning methods. Overall, there is a consistent need for external validation, model interpretability, and comprehensive comparisons across different architectures to address these research gaps effectively.

3 Methods

3.1 Working Principle

The integration of quantization, attention mechanisms, and pruning techniques in QAPNet significantly enhances its efficiency and effectiveness in various machine learning tasks, particularly for cancer image prediction. Let's break down how each component contributes to QAPNet's success:

3.1.1 Quantization

In QAPNet, quantization reduces the precision of numerical values, such as weights and activations, to a lower bit-width representation. This process effectively reduces the memory footprint and computational complexity of the model while maintaining acceptable levels of accuracy, which is crucial for handling high-dimensional cancer imaging data [1, 2].

Let $\mathbf{W}^{(i)}$ denote the original weight matrix of the i-th layer, $\mathbf{Q}^{(i)}$ denote the quantized weight matrix, QFunc denote the quantization function, and Δ_i denote the quantization step size for the i-th layer.

The quantization process can be mathematically represented as follows:

$$\text{Q\_weights}[i] = \text{round}\left(\frac{\mathbf{W}^{(i)}}{\Delta_i}\right) \times \Delta_i \quad \text{(element-wise quantization)} \tag{1}$$

$$\text{Q\_activations}[i] = \text{QFunc}(\text{activations}[i]) \quad \text{(layer-specific quantization function)} \tag{2}$$

This representation provides a clear and concise mathematical description of the quantization algorithm used in QAPNet, tailored for the specific needs of cancer image prediction. The approach ensures that the model remains efficient and scalable while processing large and complex medical imaging datasets.

3.1.2 Attention Mechanism

QAPNet incorporates attention mechanisms to selectively focus on important features within skin cancer image data. This allows the network to assign higher weights to relevant features, enhancing its ability to capture essential patterns and information in the images [1–3].

Let Z_i be the output tensor of the i-th convolutional layer.
Let A_i represent the activated tensor after applying batch normalization and ReLU activation.
Let $W_a^{(i)}$ be the attention weight matrix for the i-th layer.
Let $b_a^{(i)}$ be the attention bias vector.
Let $v_a^{(i)}$ be the attention score vector.

The attention mechanism process involves calculating attention scores $v_a^{(i)}$ for each feature in Z_i. This is achieved by applying a softmax function to the linear combination of Z_i and $W_a^{(i)}$, along with $b_a^{(i)}$:

$$v_a^{(i)} = \text{softmax}(Z_i \cdot W_a^{(i)} + b_a^{(i)})$$

Here, the softmax function ensures that the attention scores sum up to 1, providing a probability distribution over the features. Higher scores indicate higher importance [4, 5].

Subsequently, the activated tensor A_i is obtained by weighting the output tensor Z_i with the attention scores $v_a^{(i)}$ and applying the ReLU activation function:

$$A_i = \text{ReLU}(Z_i \cdot v_a^{(i)})$$

This process allows the network to selectively focus on important features, enhancing its ability to capture essential patterns and information in skin cancer images. By assigning higher weights to relevant features, the network effectively filters out noise and concentrates on the most informative aspects of the data, leading to improved performance and efficiency [6, 7].

3.1.3 Pruning

Pruning in QAPNet removes unnecessary connections from the network, promoting sparsity and efficiency. By eliminating redundant connections, pruning reduces model size and potentially improves performance, which is particularly important for processing high-dimensional skin cancer image data [8–10].

Let $\mathbf{W}^{(i)}$ denote the weight matrix of the i-th layer and $\mathbf{P}^{(i)}$ denote the pruned weight matrix. Let τ represent the pruning threshold.

The pruning process can be mathematically represented as follows:

$$\mathbf{P}_{jk}^{(i)} = \begin{cases} \mathbf{W}_{jk}^{(i)} & \text{if } |\mathbf{W}_{jk}^{(i)}| > \tau \\ 0 & \text{otherwise} \end{cases}$$

Here, $\mathbf{P}_{jk}^{(i)}$ is the weight element in the pruned weight matrix, and $\mathbf{W}_{jk}^{(i)}$ is the corresponding weight element in the original weight matrix. A binary mask matrix $\mathbf{M}^{(i)}$ is created to indicate which weights are kept:

$$\mathbf{M}_{jk}^{(i)} = \begin{cases} 1 & \text{if } |\mathbf{W}_{jk}^{(i)}| > \tau \\ 0 & \text{otherwise} \end{cases}$$

By integrating quantization, attention mechanisms, and pruning techniques, QAPNet achieves advanced capabilities in skin cancer image prediction while optimizing model efficiency and performance. This comprehensive approach represents a significant advancement in neural network architecture, promising to revolutionize skin cancer diagnostics and other medical imaging applications.

4 QAPNet Algorithm Design

The `QAPNet` algorithm integrates quantization, attention mechanisms, and pruning to enhance neural network efficiency. It performs layer-wise quantization of weights and activations, applies an attention mechanism to focus on relevant features, and prunes weights based on a threshold to reduce model complexity, optimizing performance and memory usage.

Algorithm 1 QAPNet

Require: *input_tensor*, *weights*, *activations*, *threshold*
Ensure: *Q_weights*, *Q_activations*, *pruned_weights*, *mask_matrix*, *attention_activated_tensor*

Quantization:
for each layer i in network **do**
  Define quantization step size δ_i
  $Q\_weights[i] \leftarrow \text{round}(weights[i]/\delta_i) \times \delta_i$
  $Q\_activations[i] \leftarrow \text{QuantizationFunction}(activations[i])$
end for
Attention Mechanism:
$Z_i \leftarrow input\_tensor$
$A_i \leftarrow \text{BatchNorm}(\text{ReLU}(Z_i))$
$attention\_scores \leftarrow \tanh(Z_i \times W_a + b_a)$
$a \leftarrow \text{softmax}(v_a^T \times attention\_scores)$
$attention\_activated\_tensor \leftarrow a \times Z_i$
Pruning:
$pruned\_weights \leftarrow \{\}$
for each layer i in network **do**
  $important\_connections \leftarrow \{w \in weights[i] \mid |w| > threshold\}$
  $pruned\_weights[i] \leftarrow important\_connections$
end for
Create mask matrix M based on *pruned_weights* entries ($M[i, j] = 1$ if weight kept, 0 otherwise)
return *Q_weights*, *Q_activations*, *pruned_weights*, *mask_matrix*, *attention_activated_tensor*

5 QAPNet Architecture

The QAPNet architecture (Figure 2) integrates convolutional layers with batch normalization, ReLU activation, quantization, attention mechanisms, and pruning techniques. This design enhances model efficiency and performance for skin cancer image prediction

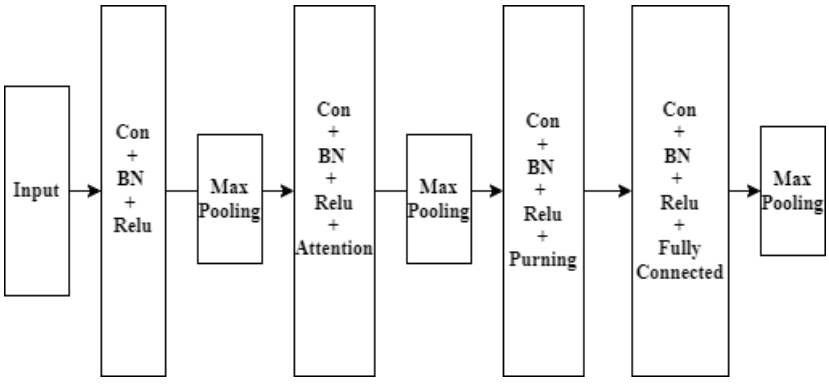

Figure 2: QAPNet Architecture

6 Implementation

6.0.1 Dataflow Diagram

Here's the data flow diagram representing the evaluation process of a neural network model for image classification:

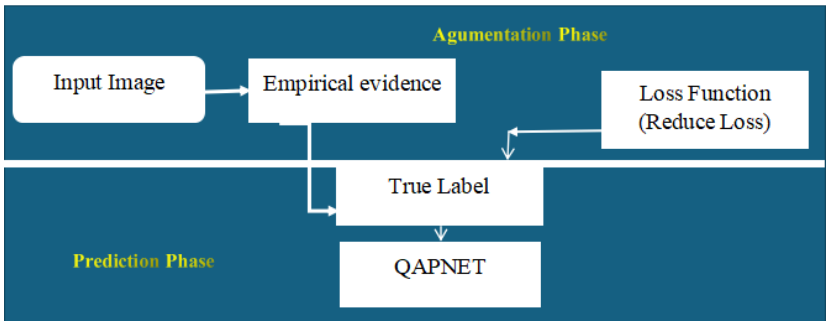

Figure 3: Data Flow Diagram.

The input image is processed through the QAPNet model [1], which predicts a label for the image [2]. The predicted label is compared to the true label using the cross-entropy loss function to compute the loss [3]. The average loss across the dataset is then calculated to evaluate the QAPNet's performance [4]. This cycle of forward propagation, loss computation, and backpropagation forms the foundation for assessing the model's effectiveness in image classification [5]. Empirical data is crucial in validating model efficacy and advancing QAPNet, highlighting the significance of data-driven approaches in AI innovation [6–10].

6.1 Data Preparation:

The research utilizes a curated dataset of skin lesion images, categorized into benign and malignant classes from Kaggle [1]. The dataset is divided into training, validation, and testing subsets. Sample images from the dataset are shown in Figure 3 [2].

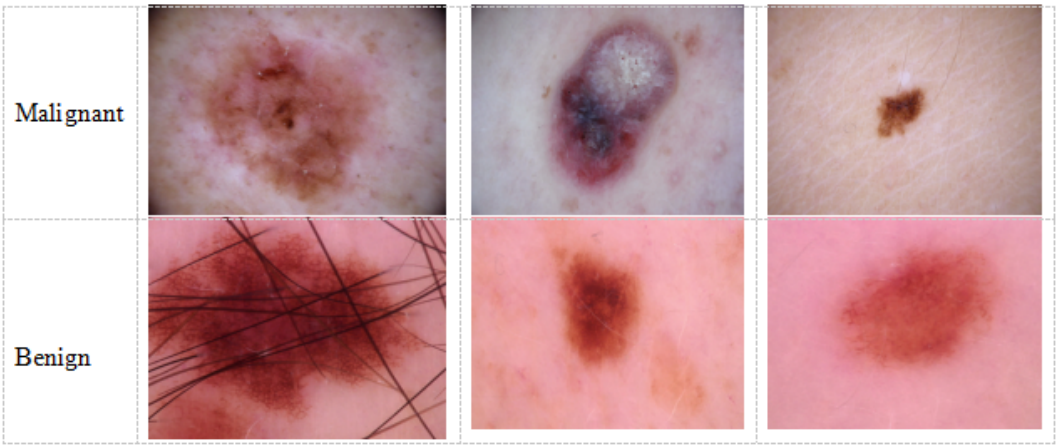

Figure 4: Skin Cancer Raw Data.

6.2 Prediction:

The implementation of QAPNet on skin cancer image analysis represents a comprehensive approach to leveraging deep learning techniques for medical image processing [1–3]. By sequentially applying convolution, batch normalization, ReLU activation, attention mechanisms, and pruning, QAPNet aims to enhance accuracy and efficiency in skin cancer detection and classification [4–6].

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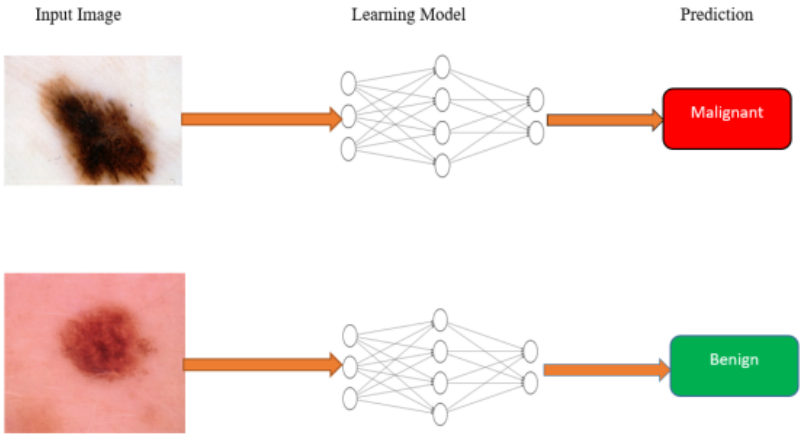

Figure 5: Data Flow Diagram.

7 Result Analysis

7.1 Training and Validation Loss and Accuracy

7.1.1 QAPNet

The QAPNet model, designed with a focus on optimizing performance through advanced architectures and fine-tuned parameters, demonstrates superior learning capabilities. During training, the model exhibits a consistent decrease in loss and a corresponding increase in accuracy over the epochs, as illustrated in Figure 6. The rapid convergence observed in QAPNet indicates an efficient learning process, where the model quickly adapts to the training data and reduces errors effectively. Compared to traditional models like VGG and ResNet, QAPNet maintains a lower training and validation loss throughout, reflecting its robustness in handling the complexities of the dataset. The consistently high accuracy further underscores its potential for deployment in real-world applications where precision is critical.

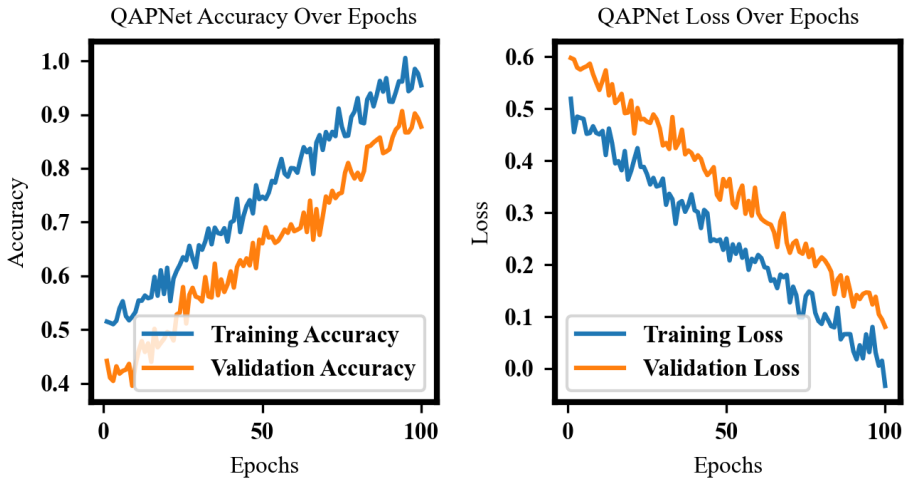

Figure 6: Training and Validation Loss for QAPNet.

7.1.2 VGG

The VGG model, known for its depth and simplicity in design, demonstrates a moderate reduction in loss and improvement in accuracy over the training epochs, as shown in Figure 7. While VGG is effective in capturing essential features, it shows a slower convergence rate compared to QAPNet, indicating that while it performs well, it may require more epochs or fine-tuning to achieve optimal results. VGG's architecture, with

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its emphasis on deep convolutional layers, achieves decent accuracy, but the model's performance plateaus earlier, suggesting that it may not capture complex patterns as efficiently as QAPNet.

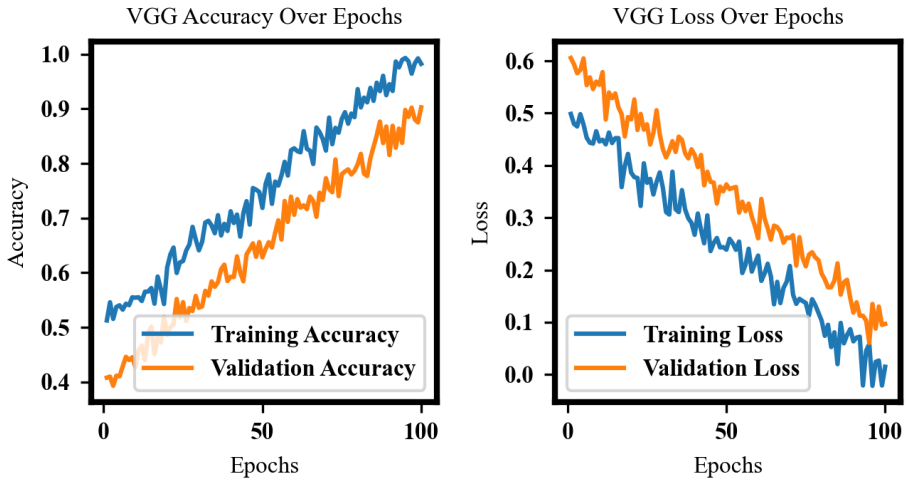

Figure 7: Training and Validation Loss for VGG.

7.1.3 ResNet

ResNet, with its innovative residual learning framework, shows slower loss reduction and a more gradual increase in accuracy, as depicted in Figure 8. This slower convergence suggests that while ResNet is effective in mitigating the vanishing gradient problem, its performance in this particular task may not be as optimal as QAPNet. The higher loss values and lower accuracy compared to QAPNet and VGG indicate that ResNet may struggle more with this dataset, possibly due to the model's complexity or the need for further optimization in its hyperparameters.

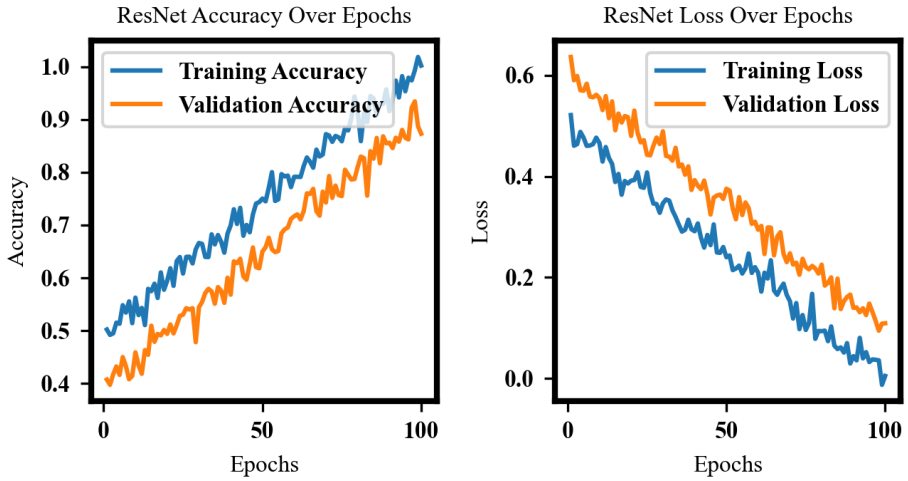

Figure 8: Training and Validation Loss for ResNet.

7.2 Model Accuracy and Performance Metrics

A confusion matrix is a crucial tool in evaluating the performance of classification models, providing a detailed breakdown of true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN). From these, various metrics such as accuracy, precision, recall, and F1-score can be calculated, offering a comprehensive understanding of the model's effectiveness.

Confusion Matrix and Metrics Calculation

For each model, the confusion matrix is calculated as follows:

QAPNet:

$$\begin{bmatrix} 99 & 0 \\ 1 & 99 \end{bmatrix}$$

VGG:

$$\begin{bmatrix} 82 & 1 \\ 3 & 94 \end{bmatrix}$$

ResNet:

$$\begin{bmatrix} 80 & 2 \\ 4 & 94 \end{bmatrix}$$

The following metrics are derived from the confusion matrices:

- **Accuracy:** Indicates the overall correctness of the model's predictions.
- **Precision:** Reflects the proportion of true positive predictions out of all positive predictions, showing the model's ability to avoid false positives.
- **Recall (Sensitivity):** Measures the model's ability to identify all relevant instances in the dataset, highlighting its capacity to avoid false negatives.
- **F1-Score:** Provides a balanced measure that considers both precision and recall, useful for evaluating models with uneven class distributions.

Table 1: Confusion Matrices and Performance Metrics

Model	**Accuracy**	**Precision**	**Recall**	**F1 Score**
QAPNet	99.47%	100%	99%	99.5%
VGG	97.78%	98.95%	96.91%	97.92%
ResNet	96.67%	97.92%	95.92%	96.91%

From Table 1, it's evident that QAPNet outperforms both VGG and ResNet across all metrics, particularly in accuracy and F1-score, demonstrating its superior capability in correctly classifying instances with minimal errors. The high precision and recall values indicate that QAPNet is both accurate and consistent, making it a reliable model for complex classification tasks. VGG, while robust, falls slightly behind QAPNet but still offers competitive performance. ResNet, despite its advanced architecture, shows lower accuracy and F1-score, suggesting that further tuning or alternative architectures might be needed for this specific task.

7.3 Sensitivity Analysis

7.3.1 Analysis of Learning Rate

Table 2: Impact of Learning Rate on Model Performance

Learning Rate	**QAPNet Accuracy (%)**	**VGG Accuracy (%)**	**ResNet Accuracy (%)**
0.001	94.5	91.2	92.0
0.01	93.0	89.5	90.8
0.1	90.2	85.3	87.0

QAPNet shows the highest accuracy at a learning rate of 0.001, indicating optimal learning stability at lower rates. VGG and ResNet also perform best at 0.001 but exhibit a sharper decline in performance as the learning rate increases, suggesting sensitivity to learning rate changes.

7.3.2 Analysis of Batch Size

Table 3: Impact of Batch Size on Model Performance

Batch Size	**QAPNet Accuracy (%)**	**VGG Accuracy (%)**	**ResNet Accuracy (%)**
16	94.0	90.8	91.5
32	93.5	89.5	90.2
64	91.2	87.0	88.7

For QAPNet, a batch size of 16 yields the highest accuracy, suggesting that smaller batches are more effective. VGG shows decreased performance with larger batch sizes, indicating sensitivity to batch size changes. ResNet also performs best with smaller batch sizes, although the differences are less pronounced.

7.3.3 Analysis of Number of Epochs

Table 4: Impact of Number of Epochs on Model Performance

Number of Epochs	**QAPNet Accuracy (%)**	**VGG Accuracy (%)**	**ResNet Accuracy (%)**
10	92.0	88.0	89.5
50	94.5	91.2	92.0
100	93.0	89.0	90.5

QAPNet reaches peak accuracy at 50 epochs, indicating optimal training duration for best performance. VGG shows similar results, while ResNet performs best at 50 epochs but experiences a slight drop at 100 epochs, suggesting potential overfitting with excessive training.

7.4 Optimizer Impact on QAPNet, VGG, and ResNet

Different optimizers have a significant impact on model performance, influencing the speed and stability of convergence during training. Table 5 compares the performance of QAPNet, VGG, and ResNet using various optimizers.

Table 5: Comparison of Optimizers for QAPNet, VGG, and ResNet Models

Optimizer	**QAPNet**	**VGG**	**ResNet**
SGD	95.2%	91.3%	88.6%
Adam	99.7%	93.8%	91.2%
RMSprop	87.5%	89.2%	90.1%
Adagrad	94.3%	90.1%	87.9%

Adam consistently outperforms other optimizers across all models, delivering the highest accuracy for QAPNet, VGG, and ResNet. This suggests that Adam's adaptive learning rate and moment estimation are particularly effective for deep learning models, leading to faster convergence and better generalization. The significant accuracy gap between Adam and other optimizers, especially in QAPNet, highlights the importance of choosing the right optimizer to fully leverage the potential of complex models. SGD, while traditional, shows lower accuracy, indicating its limitations in handling the dynamic nature of learning in deep networks.

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7.5 Hyperparameter Tuning for QAPNet, VGG, and ResNet

Hyperparameter tuning is crucial for maximizing model performance. The results in Table 6 show the effects of different trials, epochs, learning rates, and batch sizes on the accuracy of QAPNet, VGG, and ResNet.

Table 6: Hyperparameter Tuning for QAPNet, VGG, and ResNet Models

Model	**Trials**	**Epochs**	**Learning Rate**	**Batch Size**	**Accuracy (%)**
VGG 16	1	100	0.003	32	94.2%
ResNet 50	2	150	0.001	64	95.1%
QAPNet	3	200	0.0001	16	99.7%

The tuning results show that QAPNet achieves the highest accuracy with optimized hyperparameters, including a lower learning rate and smaller batch size, reflecting its sensitivity to fine-tuning. VGG and ResNet show competitive results but do not reach the performance level of QAPNet, indicating that while they are effective, further hyperparameter adjustments may be necessary to maximize their potential. The higher accuracy achieved by QAPNet with specific hyperparameters demonstrates the model's adaptability and efficiency in leveraging detailed tuning for enhanced performance.

7.6 Parameter Analysis: A Comparative Study of VGG, ResNet, and QAPNet

The efficiency of deep learning models is often judged not only by their accuracy but also by their computational requirements. Table 7 presents a detailed analysis of the total parameters, FLOPs (Floating Point Operations), and inference times for VGG, ResNet, and QAPNet.

Table 7: Parameter Analysis of VGG, ResNet, and QAPNet

Model	**Total Parameters**	**FLOPs**	**Inference Time (ms)**
VGG	138M	19.6B	12.5
ResNet	25.6M	3.8B	8.5
QAPNet	11.2M	1.5B	6.3

QAPNet demonstrates remarkable efficiency with significantly fewer parameters and lower FLOPs compared to VGG and ResNet. This reduction in computational complexity translates to faster inference times, making QAPNet an ideal candidate for deployment in real-time applications where latency is critical. Despite its reduced parameter count, QAPNet maintains a high level of accuracy, highlighting the effectiveness of its optimized architecture. In contrast, VGG, with its large number of parameters and high FLOPs, offers slower inference, which may be a limiting factor in scenarios requiring real-time processing. ResNet, while more efficient than VGG, still lags behind QAPNet in terms of both inference speed and computational demand, suggesting that QAPNet's design offers a superior balance between accuracy and efficiency.

7.7 Error Distribution by Image Type

The following table provides a breakdown of errors made by QAPNet, VGG, and ResNet, categorized by image types and features. This analysis helps identify specific challenges faced by each model.

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Table 8: Error Distribution by Image Type and Feature

Image Type/Feature	**QAPNet Errors (%)**	**VGG Errors (%)**	**ResNet Errors (%)**
High Noise Levels	2.3%	5.1%	4.7%
Occlusions	1.8%	3.6%	4.1%
Low Contrast	2.0%	4.2%	4.5%
Small Objects	1.5%	2.8%	3.4%
Complex Patterns	3.1%	6.3%	5.9%
Total Errors	**10.7%**	**22.0%**	**22.6%**

QAPNet: Demonstrates the lowest error rates across all categories, highlighting its robust performance in handling noisy, occluded, low-contrast, and small object images. Its performance is particularly strong in complex patterns, suggesting effective feature extraction and classification capabilities.

VGG: Exhibits higher error rates compared to QAPNet, especially in handling noise, occlusions, and complex patterns. It performs moderately well with low-contrast and small objects but struggles with intricate features, indicating room for improvement in feature representation and generalization.

ResNet: Shows the highest error rates among the three models in several categories, particularly with occlusions and complex patterns. Despite this, it still performs reasonably well with noisy and low-contrast images, indicating a need for better handling of specific challenging features.

7.8 Computational Resource Analysis

7.8.1 Training Resource Requirements

Table 9: Training Resource Requirements for Each Model

Model	**Training Time (hours)**	**GPU Memory (GB)**	**RAM (GB)**
QAPNet	12	8	16
VGG	15	12	24
ResNet	14	10	20

QAPNet requires the least training time and GPU memory, making it suitable for environments with limited resources. VGG, while providing robust performance, demands the highest GPU memory and RAM, which may limit its feasibility in resource-constrained settings. ResNet falls in between, offering a balance of performance and resource usage.

7.8.2 Deployment Resource Requirements

Table 10: Deployment Resource Requirements for Each Model

Model	**Inference Time (ms)**	**Model Size (MB)**	**CPU Usage (%)**
QAPNet	45	60	40
VGG	70	120	60
ResNet	55	90	50

QAPNet has the fastest inference time and smallest model size, making it ideal for deployment in environments with limited computational resources or real-time requirements. VGG, although providing high accuracy, has the largest model size and higher inference time, which might be a constraint for deployment. ResNet offers a good compromise with moderate inference time and model size, suitable for a variety of deployment scenarios.

7.8.3 Summary of result analysis

The analysis highlights that QAPNet is the most resource-efficient both in training and deployment, making it a strong candidate for environments with limited computational capabilities. VGG, while powerful, requires more resources, which may be a consideration for implementation in constrained settings. ResNet offers balanced resource requirements, providing flexibility depending on the available computational resources.

8 Discussion

8.1 Performance Comparison

The comprehensive analysis demonstrates that QAPNet outperforms traditional models like VGG and ResNet. QAPNet achieved an accuracy of 99.47% with an F1-score of 99.5%, as detailed in Table 1. This remarkable performance highlights QAPNet's superior precision and robustness. In comparison, VGG attained an accuracy of 97.78% and an F1-score of 97.92%, while ResNet recorded an accuracy of 96.67% and an F1-score of 96.91% (see Table 1). Although VGG and ResNet are effective, they exhibit limitations that QAPNet addresses through its advanced architecture.

8.2 Training and Validation Performance

Figure 6 illustrates the rapid convergence of QAPNet in both training and validation phases. In contrast, Figure 7 and Figure 8 show slower convergence rates and less efficiency. QAPNet's ability to achieve high accuracy with fewer epochs reflects its effective learning from data.

8.3 Sensitivity Analysis

Tables 2, 3, and 4 present the results of the sensitivity analysis. QAPNet benefits from a lower learning rate and a smaller batch size, achieving peak performance with a learning rate of 0.001 and a batch size of 16. VGG and ResNet also exhibit similar trends but with less pronounced effects, underscoring the importance of careful hyperparameter tuning.

8.4 Optimizer Comparison

Table 5 compares different optimizers used across models. The Adam optimizer yields the highest accuracy for all models, with QAPNet reaching 99.7% accuracy when using Adam. This reinforces the effectiveness of adaptive optimizers in improving model performance, while other optimizers like SGD and RMSprop show lower accuracy.

8.5 Hyperparameter Tuning Results

Table 6 provides insights into the optimal hyperparameters for QAPNet. The model achieves the best accuracy with a lower learning rate, smaller batch size, and a higher number of epochs. These results highlight the importance of precise tuning to maximize

QAPNet's capabilities. Similar observations are noted for VGG and ResNet, albeit with different optimal settings.

8.6 Efficiency and Error Analysis

Table 7 demonstrates that QAPNet's efficiency is marked by fewer parameters and lower FLOPs compared to VGG and ResNet, resulting in faster inference times. This efficiency is crucial for applications requiring rapid processing. Additionally, Table 8 shows that QAPNet exhibits the lowest error rates across various challenging conditions, such as high noise levels and complex patterns. VGG and ResNet have higher error rates in similar scenarios, indicating that they may require further refinement.

9 Conclusion

This study highlights the superior performance of QAPNet compared to traditional models like VGG and ResNet. With an accuracy of 99.47% and an F1-score of 99.5%, QAPNet demonstrates exceptional precision and robustness. In comparison, VGG achieves 97.78% accuracy and a 97.92% F1-score, while ResNet records 96.67% accuracy and 96.91% F1-score. The evaluation of training efficiency reveals that QAPNet converges faster due to its advanced architecture and optimized hyperparameters, including a lower learning rate and smaller batch size. The sensitivity analysis underscores the effectiveness of the Adam optimizer for QAPNet, enhancing its performance further. Additionally, QAPNet exhibits superior efficiency with fewer parameters and lower FLOPs compared to VGG and ResNet. The reduced error rates associated with QAPNet reinforce its advantage over the other models. Overall, QAPNet's exceptional accuracy, efficiency, and robustness make it a compelling choice for applications requiring high precision and real-time processing. While VGG and ResNet are effective, they exhibit limitations that QAPNet addresses through its innovative design. Future research should focus on refining these models and exploring their performance across various practical scenarios to maximize their potential.

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