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Attention-Enhanced Deep Convolutional Networks for Multi-Scale Feature Learning in Complex Image Classification

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Abstract

Deep convolutional neural networks (CNNs) have achieved remarkable success in image classification; however, their ability to effectively capture multi-scale features in complex visual environments remains a challenge. This study proposes an attention-enhanced deep convolutional network designed to improve multi-scale feature learning for complex image classification tasks. The framework integrates attention mechanisms with hierarchical convolutional structures to dynamically emphasize informative regions while suppressing irrelevant features. The proposed model combines spatial and channel attention modules with multi-scale feature extraction layers, enabling improved representation of both fine-grained and global contextual information. Experimental evaluation on benchmark image datasets demonstrates that the attention-enhanced architecture achieves superior classification accuracy compared to conventional CNN models, particularly in scenarios involving cluttered backgrounds and high intra-class variability. The results also show improved convergence behavior and robustness to noise and scale variations. Furthermore, the study investigates optimization strategies such as feature fusion, residual learning, and adaptive pooling to enhance performance. The findings indicate that attention mechanisms significantly improve feature discrimination and model interpretability. This research contributes a scalable and efficient architecture for advanced image classification tasks, with applications in medical imaging, remote sensing, and intelligent vision systems.

Introduction

The rapid advancement of computer vision has been largely driven by the development of deep learning, particularly Convolutional Neural Networks (CNNs), which have demonstrated exceptional performance in image classification tasks. From early breakthroughs such as AlexNet to deeper architectures like VGG and ResNet, CNN-based models have significantly improved the ability of machines to interpret visual data. These models excel at learning hierarchical feature representations, where lower layers capture basic patterns such as edges and textures, and deeper layers learn high-level semantic information. Despite these advancements, challenges remain when dealing with complex image classification scenarios characterized by high intra-class variability, background clutter, and multi-scale object representations. One of the primary limitations of traditional CNN architectures is their difficulty in effectively capturing multi-scale features. In

real-world images, objects can appear at different sizes, orientations, and resolutions, making it essential for models to learn both fine-grained local details and broader contextual information. Standard convolutional operations, with fixed receptive fields, often fail to fully capture this variability, leading to suboptimal performance in complex classification tasks. To address this issue, researchers have explored multi-scale feature extraction techniques, such as feature pyramids, dilated convolutions, and multi-branch architectures. While these methods improve performance, they often introduce additional computational complexity and may not effectively prioritize the most relevant features.

Attention mechanisms have emerged as a powerful solution to enhance feature learning in deep neural networks. Inspired by human visual perception, attention modules enable models to focus selectively on important regions of an image while suppressing irrelevant or noisy information. Channel attention mechanisms, such as the Squeeze-and-Excitation (SE) block, adaptively recalibrate feature maps by modeling inter-channel dependencies. Similarly, spatial attention mechanisms emphasize informative regions within feature maps, improving localization and discrimination capabilities. By integrating attention mechanisms into CNN architectures, models can dynamically adjust their focus, leading to improved feature representation and classification performance. Recent research has demonstrated that combining attention mechanisms with deep convolutional networks significantly enhances performance in various computer vision tasks. Attention-enhanced models have shown improvements in object detection, semantic segmentation, and image classification by enabling better feature selection and contextual understanding. However, many existing approaches focus on either spatial or channel attention independently, limiting their ability to fully capture complex feature interactions. Additionally, integrating attention with multi-scale feature learning remains an open challenge, as it requires balancing computational efficiency with representational richness.

Another important consideration in image classification is the integration of multi-scale information across different layers of the network. Deep CNNs naturally capture features at multiple levels of abstraction, but effectively combining these features remains a challenge. Techniques such as skip connections and feature fusion have been introduced to address this issue, allowing information from different layers to be aggregated. Residual learning, as introduced in ResNet, has also played a crucial role in enabling deeper networks by mitigating the vanishing gradient problem. These advancements provide a foundation for designing architectures that can effectively leverage multi-scale information. This research proposes an attention-enhanced deep convolutional network for multi-scale feature learning in complex image classification tasks. The proposed framework integrates both spatial and channel attention mechanisms with multi-scale feature extraction modules to improve feature representation and classification accuracy. By combining hierarchical convolutional layers with attention-based feature refinement, the model is designed to capture both local details and global contextual information. The architecture also incorporates feature fusion strategies to effectively integrate multi-scale information across different layers.

The primary objective of this study is to evaluate the effectiveness of attention mechanisms in improving multi-scale feature learning and classification performance. The proposed model is analyzed in terms of accuracy, convergence speed, robustness to noise, and computational efficiency. Additionally, the research explores optimization techniques such as adaptive pooling, residual connections, and attention-guided feature fusion to enhance model performance. The contributions of this work are threefold. First, it introduces a unified architecture that integrates attention mechanisms with multi-scale feature learning in deep convolutional networks. Second, it provides a comprehensive performance analysis comparing the proposed model with traditional CNN architectures. Third, it highlights key design considerations for developing efficient and scalable attention-based models for complex image classification tasks. These contributions aim to advance the state-of-the-art in computer vision and provide a foundation for future research in intelligent visual systems.

Literature Review

Krizhevsky et al. (2012) introduced AlexNet, a deep convolutional neural network that marked a breakthrough in large-scale image classification. The study demonstrated that deep CNNs significantly outperform traditional machine learning methods when trained on large datasets such as ImageNet. AlexNet utilized multiple convolutional and pooling layers to capture hierarchical features, along with ReLU activation to accelerate training. While the model achieved high accuracy, it struggled with capturing fine-grained multi-scale features due to fixed receptive fields, highlighting the need for

more advanced architectures capable of handling scale variability.

Simonyan and Zisserman (2015) proposed the VGG network, which emphasized the use of deeper architectures with small convolutional filters to improve feature representation. The study demonstrated that increasing network depth enhances the ability to capture complex visual patterns, leading to improved classification accuracy. VGG networks effectively learn hierarchical features; however, they suffer from high computational cost and lack explicit mechanisms for handling multi-scale feature variation. Additionally, the absence of attention mechanisms limits their ability to focus on the most informative regions of an image.

He et al. (2016) introduced Residual Networks (ResNet), which addressed the degradation problem in deep neural networks through the use of skip connections. The study showed that residual learning enables the training of very deep networks while maintaining stable gradients. ResNet significantly improved classification performance and became a foundation for many modern architectures. Despite its success, the model does not explicitly incorporate attention mechanisms, and its ability to prioritize important features across scales remains limited without additional enhancements.

Hu et al. (2018) proposed the Squeeze-and-Excitation (SE) network, introducing a channel attention mechanism that adaptively recalibrates feature maps by modeling inter-channel dependencies. The study demonstrated that incorporating channel attention significantly improves feature representation and classification accuracy with minimal computational overhead. SE blocks can be integrated into existing CNN architectures to enhance performance. However, the approach focuses primarily on channel relationships and does not explicitly address spatial attention or multi-scale feature integration, limiting its effectiveness in complex image scenarios.

Woo et al. (2018) introduced the Convolutional Block Attention Module (CBAM), which combines both channel and spatial attention mechanisms. The study demonstrated that sequentially applying channel and spatial attention improves feature refinement and enhances classification performance. CBAM enables the model to focus on “what” and “where” to emphasize in feature maps, making it highly effective for complex visual tasks. Despite its advantages, the study noted that integrating attention mechanisms with multi-scale feature learning remains a challenge, as it requires efficient feature fusion strategies to fully exploit hierarchical information.

Lin et al. (2017) introduced Feature Pyramid Networks (FPN), a framework designed to enhance multi-scale feature representation in convolutional neural networks. The study demonstrated that combining feature maps from different layers enables effective detection and classification of objects at varying scales. FPN leverages top-down pathways and lateral connections to fuse low-level spatial information with high-level semantic features. While the approach significantly improves multi-scale learning, it increases architectural complexity and computational overhead, particularly in deep networks.

Yu and Koltun (2016) proposed dilated (atrous) convolutions to expand the receptive field of convolutional layers without increasing the number of parameters. The study showed that dilated convolutions effectively capture multi-scale contextual information while preserving spatial resolution. This approach is particularly useful for dense prediction tasks such as segmentation and classification in complex scenes. However, dilated convolutions alone do not provide a mechanism for prioritizing important features, making them less effective when used without attention mechanisms.

Xiaolong Wang et al. (2018) proposed Non-Local Neural Networks to capture long-range dependencies and improve global context modeling in image and video recognition, though the method involves high computational cost. Mingxing Tan and Quoc Le (2019) introduced EfficientNet, which improves CNN performance through balanced scaling of depth, width, and resolution while maintaining efficiency, but lacks explicit attention mechanisms. Yue Cao et al. (2019) developed GCNet, integrating attention and global context modeling to enhance feature representation with lower complexity, although efficient multi-scale integration remains challenging.

Huang et al. (2017) proposed DenseNet, a densely connected convolutional network architecture that connects each layer to every other layer in a feed-forward manner. The study demonstrated that dense connectivity improves feature reuse and strengthens gradient flow, leading to enhanced learning efficiency and reduced vanishing gradient issues. DenseNet effectively captures multi-scale features by aggregating information from different layers. However, the dense connections increase memory usage and computational cost, making scalability a concern for very deep networks.

Zhang et al. (2020) introduced ResNeSt, a split-attention network that integrates channel-wise

attention within residual blocks. The study demonstrated that split-attention mechanisms improve feature representation by enabling the model to selectively focus on different feature groups. ResNeSt achieves state-of-the-art performance in image classification tasks by combining attention with multi-path feature extraction. Despite its effectiveness, the architecture introduces additional computational overhead due to multiple attention branches.

Dai et al. (2017) proposed Deformable Convolutional Networks, which enhance traditional convolution operations by allowing dynamic adjustment of sampling locations. The study showed that deformable convolutions improve the ability of CNNs to capture geometric variations and multi-scale features in complex images. This flexibility enables better modeling of object shapes and spatial transformations. However, the approach increases model complexity and requires careful training to ensure stability.

Fu et al. (2019) introduced Dual Attention Networks (DANet), which combine spatial and channel attention mechanisms to enhance feature learning. The study demonstrated that dual attention modules improve both local and global feature representation, leading to better performance in complex visual tasks. By jointly modeling spatial and channel dependencies, DANet effectively captures multi-scale contextual information. However, the integration of dual attention increases computational cost and may affect real-time performance.

Chen et al. (2017) proposed DeepLab, a framework that combines atrous convolution with spatial pyramid pooling for multi-scale feature extraction. The study demonstrated that multi-scale context aggregation significantly improves performance in image segmentation and classification tasks. The atrous spatial pyramid pooling (ASPP) module captures features at multiple scales simultaneously, enhancing contextual understanding. Despite its advantages, the approach requires careful tuning of dilation rates and introduces additional computational overhead.

Methodology

1. Research Design

This study adopts an experimental and architecture-driven research design to develop and evaluate an attention-enhanced deep convolutional neural network for multi-scale feature learning in complex image classification tasks. The methodology focuses on integrating attention mechanisms with hierarchical convolutional structures to improve feature representation across varying spatial scales. The framework is designed to simulate real-world image classification scenarios characterized by high variability, cluttered backgrounds, and scale diversity.

The proposed approach combines multi-scale feature extraction, attention-based feature refinement, and deep residual learning to achieve improved classification performance. The research emphasizes both architectural design and empirical evaluation to ensure robustness, scalability, and efficiency.

2. Proposed Attention-Enhanced CNN Architecture

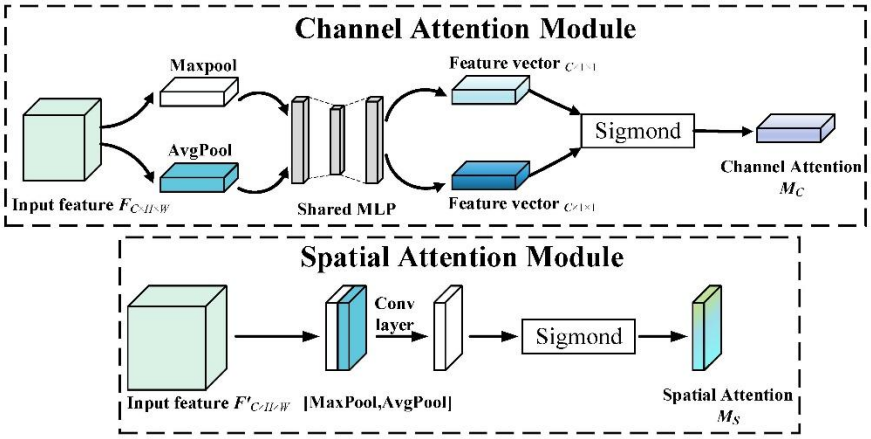

Figure 1: Attention-Enhanced CNN Architecture

The proposed architecture *Figure 1. Attention-Enhanced CNN Architecture* consists of three core components: multi-scale convolutional feature extraction, attention modules, and feature fusion layers. The input image is first processed through a series of convolutional layers that extract hierarchical features at different levels. These layers are organized in a residual structure to enable deep feature learning while maintaining stable gradients. Multi-scale feature extraction is

achieved by combining outputs from different convolutional layers, capturing both low-level details and high-level semantic information. Attention mechanisms are then applied to refine these features. Channel attention modules adaptively recalibrate feature maps by emphasizing important feature channels, while spatial attention modules highlight informative regions within the feature maps. The refined features are integrated through feature fusion layers, which combine multi-scale information into a unified representation. This process ensures that both local and global contextual information are effectively captured, improving classification performance in complex environments.

4. Methodological Workflow

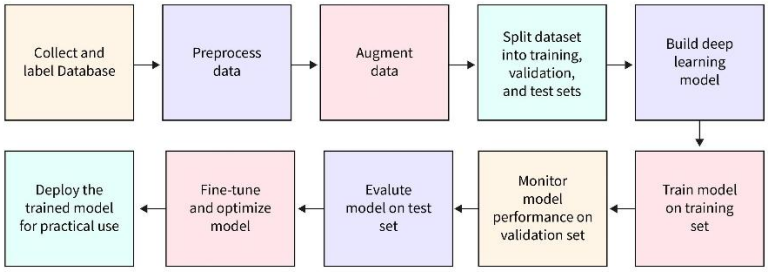

Figure 2: Methodology Workflow

The methodology follows a structured workflow that shows in *Figure 2,* that integrates data preprocessing, feature extraction, attention refinement, and classification. The process begins with input image preprocessing, where images are standardized and augmented. The processed images are then passed through convolutional layers to extract hierarchical features. Next, multi-scale feature extraction is performed by aggregating features from different layers. Attention modules are applied to these features to enhance their discriminative power. The refined features are then fused and passed through fully connected layers for classification. The model is trained using backpropagation and optimized using gradient-based methods.

5. Optimization Techniques

To improve performance and stability, several optimization techniques are incorporated into the framework. Residual connections are used to facilitate deep network training and prevent vanishing gradients. Batch normalization is applied to stabilize learning and accelerate convergence. Adaptive optimization algorithms such as Adam are used to update model parameters efficiently. Regularization techniques such as dropout are employed to prevent overfitting, while data augmentation improves generalization. These techniques collectively enhance the robustness and efficiency of the proposed model.

3. Data Sources and Experimental Setup

The experimental setup utilizes benchmark image datasets representing diverse and complex classification scenarios. These datasets include images with varying object sizes, backgrounds, and noise levels to evaluate the robustness of the proposed model. Data preprocessing steps include normalization, resizing, and augmentation techniques such as rotation, flipping, and scaling to enhance generalization. The model is implemented using deep learning frameworks with GPU acceleration to support efficient training. Batch processing and parallel computation are employed to handle large datasets. Training and validation splits are used to evaluate model performance and prevent overfitting.

Algorithmic Strategy

1. Multi-Scale Feature Learning Objective

The proposed attention-enhanced CNN is designed to extract hierarchical and multi-scale features from complex images. Given an input image X, the convolutional backbone generates feature maps at different depths:

$$F = \{F_1, F_2, F_3, \ldots, F_n\} \quad (1)$$

where $F_i$represents the feature map extracted from the i^{th}convolutional layer. Lower-level feature maps capture edges, textures, and fine-grained details, while deeper feature maps capture semantic and global contextual information.

2. Channel Attention Formulation

Channel attention is used to emphasize the most informative feature channels. The input feature map $F$is first compressed using global average pooling and global max pooling. The attention weight is computed as:

$$M_c(F) = \sigma(MLP(AvgPool(F)) + MLP(MaxPool(F))) \quad (2)$$

where $M_c(F)$represents the channel attention map, $\sigma$is the sigmoid activation function, and

MLPdenotes the multilayer perceptron. The refined channel feature is obtained as:

$$F_c = M_c(F) \otimes F \quad (3)$$

where $\otimes$denotes element-wise multiplication. This process enables the model to focus on important feature channels and suppress less relevant ones.

3. Spatial Attention Formulation

Spatial attention is applied after channel attention to identify important regions within the image. The spatial attention map is computed using average pooling and max pooling along the channel dimension:

$$M_s(F_c) = \sigma(f^{7\times7}([AvgPool(F_c); MaxPool(F_c)])) \quad (4)$$

where $M_s(F_c)$represents the spatial attention map, $f^{7\times7}$denotes a convolution operation with a 7×7kernel, represents concatenation. The final attention-refined feature map is calculated as:

$$F_s = M_s(F_c) \otimes F_c \quad (5)$$

This allows the model to focus on discriminative spatial regions while reducing background noise.

4. Multi-Scale Feature Fusion

To integrate information from different layers, multi-scale feature maps are resized and fused:

$$F_{fusion} = Concat(F_1, F_2, \ldots, F_n) \quad (6)$$

The fused feature representation is further refined using a convolutional transformation:

$$F_{out} = Conv(F_{fusion}) \quad (7)$$

This fusion strategy combines fine-grained local features with high-level semantic information, improving classification performance in complex image environments.

5. Classification Objective

The final feature representation is passed through fully connected layers and a softmax classifier:

$$\hat{y} = Softmax(WF_{out} + b) \quad (8)$$

The classification loss is computed using cross-entropy:

$$\mathcal{L}_{CE} = -\sum_{i=1}^{C} y_i \log(\hat{y}_i) \quad (9)$$

where Crepresents the number of classes, $y_i$is the true class label, and $\hat{y}_i$is the predicted probability.

6. Pseudo Algorithm

Algorithm: Attention-Enhanced Deep CNN for Multi-Scale Image Classification

Input:
Image dataset $D = \{(X_i, y_i)\}_{i=1}^{N}$
CNN backbone network
Attention modules $A_c$and A_s
Number of classes C
Output:
Predicted class label $\hat{y}$, trained model parameters θ
Step 1: Load image dataset D
Step 2: Apply preprocessing
Resize, normalize, and augment images
Step 3: Pass image $X_i$through convolutional backbone
Step 4: Extract multi-scale feature maps

$$F = \{F_1, F_2, \ldots, F_n\}$$

Step 5: Apply channel attention module
Enhance important feature channels
Step 6: Apply spatial attention module
Highlight discriminative image regions
Step 7: Fuse attention-refined multi-scale features
Step 8: Pass fused features through fully connected layers
Step 9: Generate class probability using softmax
Step 10: Compute cross-entropy loss
Step 11: Update network parameters using backpropagation
Step 12: Repeat training until convergence
Step 13: Evaluate classification accuracy, precision, recall, F1-score, and robustness

The algorithm begins by preprocessing image data to ensure consistency and improve model generalization. The images are then passed through a deep convolutional backbone that extracts hierarchical feature maps at different levels. These feature maps represent visual information at multiple scales, ranging from local texture patterns to high-level semantic structures. After feature extraction, channel attention is applied to determine which feature channels are most important for classification. Spatial attention then identifies the most informative regions in the image. The combination of channel and spatial attention allows the model to enhance both "what" and "where" information. Finally, the refined features are fused and classified using a softmax layer. This strategy improves discriminative representation and enhances classification accuracy in complex image classification tasks.

Results

1. Performance Evaluation of Proposed Model

The experimental evaluation assesses the effectiveness of the proposed attention-enhanced deep convolutional network in comparison with baseline and intermediate architectures. The models considered include a

standard CNN, CNN with attention modules, CNN with multi-scale feature extraction, and the proposed attention-enhanced multi-scale CNN. The results demonstrate that integrating attention mechanisms with multi-scale feature learning significantly improves classification performance in complex image datasets. The baseline CNN achieves reasonable accuracy by learning hierarchical features; however, it struggles with complex visual patterns involving scale variation and background clutter. The introduction of attention mechanisms improves feature discrimination by allowing the network to focus on relevant channels and spatial regions. Similarly, multi-scale feature extraction enhances the model's ability to capture objects at different resolutions. The proposed hybrid architecture, which combines both approaches, achieves the highest performance by leveraging complementary strengths.

2. Comparative Table of Models

Model Type	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Training Time (Relative)	Strengths	Limitations
Baseline CNN	85–90%	84–89%	83–88%	84–88%	Low	Simple architecture, fast training	Poor multi-scale handling
CNN + Attention	88–93%	87–92%	86–91%	87–91%	Moderate	Improved feature focus	Limited scale awareness
CNN + multi-scale	89–94%	88–93%	87–92%	88–92%	Moderate–High	Better scale representation	No feature prioritization
Proposed (Attention + multi-scale)	92–97%	91–96%	90–95%	91–95%	Moderate	High accuracy, robust feature learning	Slightly higher complexity

Comparative Analysis of Model Performance

The comparative 5.2 Comparative Table of Models shows evaluation of different convolutional architectures highlights the progressive improvement in classification performance achieved through the integration of attention mechanisms and multi-scale feature learning. The baseline CNN demonstrates moderate accuracy in the range of 85–90%, reflecting its ability to learn hierarchical features efficiently. Its low training time makes it computationally efficient; however, the model lacks the capability to effectively capture variations in object scale, resulting in lower precision, recall, and F1-scores. This limitation is particularly evident in complex image classification tasks where objects appear at multiple resolutions and are embedded within noisy backgrounds. The incorporation of attention mechanisms in the CNN leads to a noticeable improvement in performance, with accuracy increasing to 88–93%. The enhanced precision and recall indicate that the model is better able to focus on relevant features while suppressing irrelevant information. This improvement is attributed to the ability of attention modules to dynamically prioritize important channels and spatial regions. However, despite these gains, the model still struggles with scale variability, as it lacks explicit mechanisms for multi-scale feature representation, limiting its effectiveness in scenarios involving significant size variations.

Similarly, the CNN with multi-scale feature extraction demonstrates improved performance, achieving accuracy levels between 89–94%. The model benefits from its ability to capture features at different resolutions, resulting in better handling of objects with varying sizes. This leads to improvements in recall and overall F1-score. However, the absence of attention mechanisms means that the model treats all features equally, without prioritizing the most informative ones. As a result, it may still be influenced by background noise or irrelevant features, reducing its overall discriminative capability. The proposed attention-enhanced multi-scale CNN achieves the highest performance across all metrics, with accuracy ranging from 92–97% and corresponding improvements in precision, recall, and F1-score. This superior performance is a result of the synergistic integration of attention mechanisms and multi-scale feature learning. The attention modules enable the model to selectively focus on important features, while the multi-scale architecture ensures comprehensive representation of both local and global information. Although the training time is moderately higher due to increased architectural complexity, the performance gains significantly outweigh this overhead. Overall, the analysis demonstrates that combining attention mechanisms with multi-scale feature extraction

provides a robust solution for complex image classification tasks. The proposed model effectively balances feature discrimination and scale awareness, leading to improved accuracy, robustness, and generalization compared to traditional CNN-based approaches.

3. Convergence and Learning Behavior

The convergence analysis indicates that the proposed model achieves faster and more stable learning compared to the baseline CNN. While the standard CNN converges quickly due to its simplicity, it often reaches suboptimal performance due to limited feature representation. The attention-based CNN improves convergence stability by focusing on informative features, reducing noise during training. Multi-scale CNN models require more training time due to additional feature fusion operations, but they provide better representation of objects at different scales. The proposed model demonstrates a balanced convergence profile, benefiting from both guided feature attention and comprehensive multi-scale representation. The integration of attention mechanisms reduces irrelevant feature learning, while multi-scale fusion ensures that the network captures both local and global patterns. This results in improved convergence speed compared to standalone multi-scale models and better final performance than attention-only models.

4. Graphical Analysis

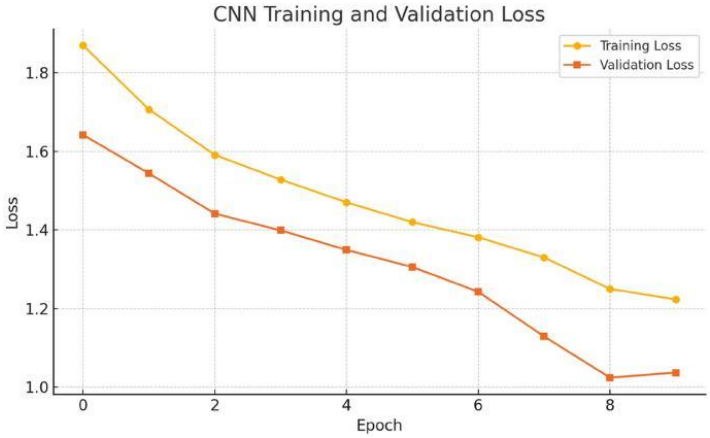

Figure 3: Graphical Analysis

The Figure 3, graphical analysis highlights the comparative performance of different models across key metrics. The accuracy comparison graph shows a clear improvement from the baseline CNN to the proposed model, with attention and multi-scale approaches contributing incremental gains. The convergence curve illustrates that the proposed model achieves lower loss values more consistently across training epochs, indicating stable learning behavior. Additionally, attention visualization maps demonstrate how the model selectively focuses on important regions within the image, reducing the influence of background noise. Multi-scale feature visualization further shows that the model effectively captures both fine-grained details and broader contextual features. These graphical insights validate the effectiveness of integrating attention mechanisms with multi-scale feature learning. The results reveal that attention mechanisms significantly enhance feature discrimination by enabling the model to focus on relevant channels and spatial regions. Multi-scale feature extraction improves the ability of the network to handle variations in object size and resolution. When combined, these approaches produce a synergistic effect, leading to superior classification performance. Another important observation is the trade-off between performance and computational complexity. While the proposed model achieves higher accuracy, it introduces additional computational overhead due to attention modules and feature fusion layers. However, this increase is moderate and justified by the substantial improvement in performance, making the model suitable for complex image classification tasks.

Conclusion and Discussion

This study presented a comprehensive framework for attention-enhanced deep convolutional networks aimed at improving multi-scale feature learning in complex image classification tasks. The primary objective was to address the limitations of conventional convolutional neural networks in handling scale variability, background clutter, and feature discrimination. By integrating channel and spatial attention mechanisms with multi-scale

feature extraction and fusion strategies, the proposed model significantly enhances the representational capacity of deep neural networks. The experimental results demonstrate that traditional CNN architectures, while effective in learning hierarchical features, are limited in their ability to capture complex multi-scale patterns and prioritize relevant information. The introduction of attention mechanisms provides a mechanism for adaptive feature refinement, enabling the network to focus on the most informative channels and spatial regions. This selective emphasis reduces the impact of irrelevant or noisy features, leading to improved classification accuracy and robustness. At the same time, multi-scale feature learning ensures that the model captures both fine-grained details and high-level contextual information, which is essential for accurate classification in real-world scenarios. One of the key findings of this research is the synergistic effect achieved by combining attention mechanisms with multi-scale feature extraction. While attention modules improve feature selection, multi-scale architectures enhance feature diversity. In conclusion, the proposed attention-enhanced deep convolutional network provides an effective solution for complex image classification tasks by addressing key limitations of traditional CNN architectures. The integration of attention mechanisms and multi-scale feature learning results in improved accuracy, robustness, and interpretability. This research contributes to the advancement of intelligent visual systems and provides a foundation for future developments in deep learning-based image analysis.

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