Attention-Enhanced VGG16 with Transfer Learning for Multi-Class Image Classification

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***Abstract*—Accurate multi-class image classification is a fundamental requirement for reliable visual recognition systems. This work presents a deep learning–based classification framework built on the VGG16 convolutional neural network and evaluated on a custom dataset comprising five heterogeneous classes: Car, Building, Person, Tree, and Lab. A baseline model trained with randomly initialized weights is used for performance comparison. The proposed approach enhances the baseline by integrating an attention mechanism and, in a subsequent experimental setting, applying transfer learning from the ImageNet dataset with fine-tuning. Experimental results, evaluated using standard classification metrics, demonstrate that the enhanced model outperforms the baseline in terms of classification accuracy and training stability,showing the effectiveness of attention mechanisms and pretrained representations for multi-class image classification. [1].**

I. Introduction

Machine learning, as a core branch of artificial intelligence (AI), aims to develop models that can learn patterns from data and improve performance without explicit programming. Within this field, deep learning has achieved notable success through multi-layer neural networks capable of modeling complex visual representations. Convolutional Neural Networks (CNNs), in particular, have become the standard architecture for image classification tasks due to their ability to automatically learn hierarchical features from raw images. CNN-based models eliminate the need for handcrafted feature extraction and enable end-to-end learning. This capability makes them highly effective for handling visual data with complex spatial structures. Consequently, CNNs form the foundation of modern image classification systems, including the VGG16-based framework adopted in this study. [2].

Automatic image classification in real-world scenarios remains a challenging task when dealing with visually heterogeneous object categories. In this study, the dataset consists of five distinct classes: Car, Building, Person, Tree, and Lab, which exhibit substantial variation in shape, texture, scale, and visual context. This high inter-class diversity increases the difficulty of learning robust and generalizable feature representations using conventional deep learning models. Models trained from randomly initialized weights are particularly prone to overfitting, as they may memorize class-specific patterns rather than learning discriminative features that generalize well to unseen data. This limitation becomes evident when high training accuracy does not translate into stable validation or test performance. Therefore, the key challenge is to design a classification framework that effectively captures meaningful visual representations across diverse classes while maintaining reliable generalization and training stability. [3].

Despite the progress achieved by deep learning models in image classification, there is a noticeable lack of models specifically suited for datasets of moderate size that contain highly diverse visual categories. Most existing architectures are either designed to scale with very large datasets or require extensive data to achieve stable and reliable performance. When applied to moderately sized datasets with heterogeneous classes, these models often struggle to generalize effectively, leading to overfitting or unstable learning behavior. Furthermore, high visual diversity across classes increases the difficulty of learning discriminative features without sufficient data support. As a result, existing models may fail to deliver consistent performance when handling datasets that are neither small nor large but exhibit substantial inter-class variation. [4].

To address these gaps, this study employs the VGG16 architecture as the core backbone for multi-class image classification and establishes a controlled experimental pipeline for systematic evaluation. Baseline models are first trained from scratch using VGG16 with randomly initialized weights and a fully trainable backbone, while varying only the configuration of the classification head. An enhanced VGG16-based configuration is then examined by integrating an attention [16] mechanism and a hybrid pooling strategy to refine feature representations. This model is trained in two stages, beginning with training the classification head while freezing the backbone, followed by fine-tuning using a reduced learning rate. In addition, a transfer learning setup based on ImageNet-pretrained VGG16 is investigated. This structured approach enables a clear and fair comparison of different training strategies and their impact on classification performance across heterogeneous classes. [5].

II. Related Work

Transfer learning with convolutional neural networks (CNNs) has become a dominant approach for multi-class image classification, particularly when datasets are limited, moderately sized, or imbalanced. Recent studies across medical imaging, industrial inspection, agriculture, and remote sensing consistently report that reusing ImageNet-pretrained backbones provides strong feature representations and improves convergence and generalization compared with training from scratch [11].

Common CNN backbones widely adopted in the literature include VGG16 and VGG19, ResNet variants (such as ResNet18, ResNet50, ResNet152, and ResNet50V2), DenseNet architectures (e.g., DenseNet121 and DenseNet201), Inception-based models, Xception, MobileNetV2, EfficientNet variants, and AlexNet. Comparative and application-driven studies consistently report that fine-tuning these pretrained architectures leads to strong performance in multi-class classification tasks [2], [3], [4]. For instance, hybrid transfer learning approaches combining ResNet50V2, MobileNetV2, and DenseNet121 have achieved high accuracy in multi-class brain tumor recognition [1]. Similarly, AlexNet-based transfer learning has demonstrated competitive results for multi-class brain image classification without relying on handcrafted features [3]. In ophthalmology, VGG16-based transfer learning frameworks have shown strong performance in multi-class and multi-label fundus image classification [5]. Moreover, studies in industrial security imagery confirm the effectiveness of pretrained CNNs such as AlexNet and VGG, including configurations that utilize CNNs as feature extractors in conjunction with classical classifiers. [14], [19]. [12].

Prior studies indicate that multi-class classification performance is strongly influenced by both the selected CNN backbone and the adopted training strategy, particularly when datasets are moderately sized or exhibit class imbalance. Common approaches include fine-tuning pretrained models or using CNN backbones as feature extractors combined with task-specific classifiers, as these strategies often improve convergence and generalization compared to training from scratch [2], [3]. Motivated by these findings, and following preliminary experiments with alternative architectures such as ResNet18 and EfficientNet, this study adopts VGG16 to enable a clear and controlled comparison between different training configurations. Specifically, a baseline model with randomly initialized weights is contrasted against a transfer learning setup using ImageNet-pretrained VGG16 with fine-tuning. This design facilitates an objective evaluation of training-from-scratch versus transfer learning on a dataset comprising five visually diverse classes: Car, Person, Tree, Building, and Lab.

III. Dataset

The dataset used in this study is referred to as the *VGG16-Based Multi-Class Image Dataset* [1]. It consists of natural RGB images collected for the purpose of multi-class image classification. The dataset contains five visually diverse classes, namely *Car*, *Person*, *Tree*, *Building*, and *Lab* [**?**]. Images exhibit substantial variations in spatial resolution, background complexity, object scale, and illumination conditions, which increases the difficulty of the classification task and reflects realistic visual scenarios [3].

Prior to model training, duplicate images were identified and removed to prevent data leakage and bias [4]. After this cleaning process, the dataset showed class imbalance, which motivated the use of data augmentation to achieve balanced learning [5].

A. Dataset Organization

The dataset is organized using a class-based directory structure, where each class is stored in a separate folder. This structure allows automated label assignment when loading the data using deep learning frameworks [3]. After preprocessing and duplicate removal, the number of images per class before augmentation is summarized in Table I.

TABLE I: Number of images per class before augmentation

Class	**Number of Images**
Building	425
Car	448
Lab	401
Person	424
Tree	470
Total	2168

The dataset was divided into training, validation, and testing subsets using fixed random seeds to ensure reproducibility [1]. This split allows objective evaluation of the model's generalization capability on unseen data.

B. Image Preprocessing

All images were resized to a fixed resolution of 224 × 224 pixels to match the input requirements of the VGG16 architecture [3]. Images were maintained in RGB format and normalized by rescaling pixel values to the [0, 1] range. No ImageNet-based preprocessing, such as mean subtraction or channel reordering, was applied since the VGG16 backbone was trained from scratch without pre-trained weights. This approach allows the model to learn dataset-specific features directly from the provided images. Additionally, data augmentation techniques, including random rotations, horizontal flipping, width and height shifts, zooming, and brightness adjustments, were applied to the training set to enhance generalization and mitigate potential class imbalance issues.

C. Class Balancing via Data Augmentation

Due to the observed class imbalance, data augmentation was applied only to the training set in order to balance all classes to the size of the largest class (470 images) [5]. For each class c with N_c samples, the number of augmented images was computed as:

$$N_{\text{aug}} = N_{\max} - N_c$$

where $N_{\max}$ denotes the number of images in the largest class.

Augmentation techniques included random rotations, horizontal flipping, width and height shifts, and zooming [3]. These transformations preserve semantic content while increasing intra-class variability, thereby improving generalization and reducing overfitting.

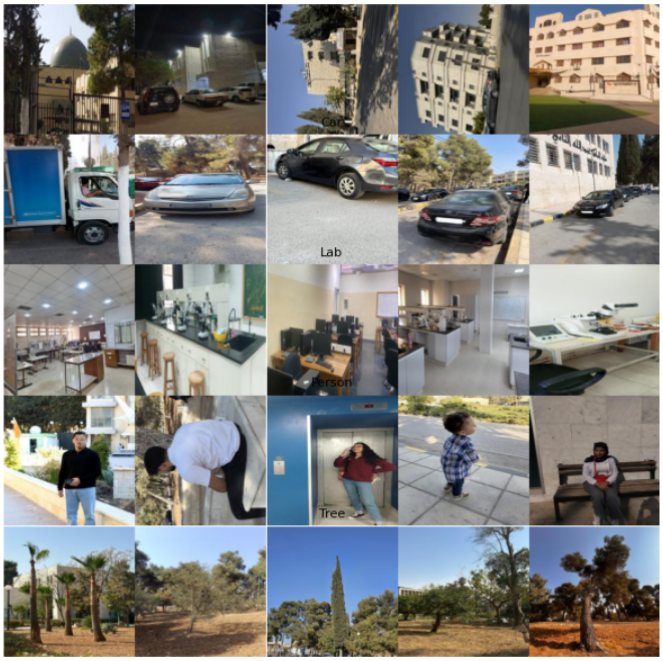

Fig. 1: Example images from each class in the VGG16-Based Multi-Class Image Dataset demonstrating intra-class variability [1].

IV. Methodology

This section presents the proposed deep learning framework for multi-class image classification based on the VGG16 convolutional neural network. The methodology is designed to align precisely with the implemented training pipeline and supports both training from scratch and transfer learning configurations. It emphasizes efficient feature extraction, balanced learning, and stable optimization. The framework enables a controlled baseline training setup, followed by performance enhancement through transfer learning and novel data augmentation strategies, ensuring robust generalization across diverse image classes [4].

A. Problem Definition

The task is formulated as a five-class classification problem. Given an input image

$$x \in R^{224\times224\times3},$$

the objective is to predict a class label

$$y \in \{\text{Car}, \text{Person}, \text{Tree}, \text{Building}, \text{Lab}\}.$$

The model learns a mapping function

$$f_\theta : x \to \hat{y},$$

where $\hat{y}$ represents a probability distribution over the five classes obtained using a Softmax function [3].

B. Overall Framework

The proposed framework consists of image preprocessing, feature extraction using VGG16 backbone, classification through custom fully connected layers, and performance evaluation on a held-out test set [5]. Figure 2 illustrates the architecture of the VGG16 network used in this work.

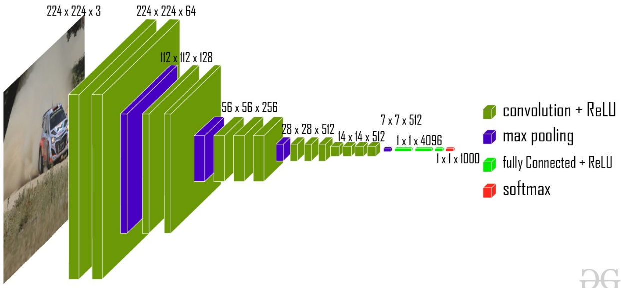

Fig. 2: Architecture of the VGG16 convolutional neural network illustrating stacked convolutional layers and pooling operations used for feature extraction [**?**].

C. Feature Extraction Using VGG16

VGG16 is a deep convolutional neural network architecture composed of 13 convolutional layers organized into five convolutional blocks, each followed by a max-pooling layer. In this study, the original fully connected classification layers of VGG16 were removed by setting `include_top=False`, and only the convolutional backbone was retained.

The VGG16 network was initialized *without pre-trained weights* (`weights=None`) and trained from scratch on the target dataset. This design choice enables the model to learn feature representations that are specifically tailored to the characteristics of the dataset. All convolutional layers were initially set to be trainable, allowing the network to effectively capture low-level and mid-level visual features such as edges, textures, and structural patterns relevant to the classification task [15].

D. Classification Head and Fine-Tuning Strategy

A custom classification head was appended to the VGG16 backbone. This head begins with a Global Average Pooling layer, which reduces the spatial dimensionality of the feature maps while preserving discriminative information. A Dropout layer with a rate of 0.2 was subsequently applied to mitigate overfitting. This was followed by a fully connected Dense layer with 128 neurons and ReLU activation to enhance feature discrimination. The final classification layer consists of a Dense layer with five neurons and Softmax activation, enabling multi-class classification.

To further improve generalization performance, a fine-tuning strategy was employed. Specifically, the lower layers of the VGG16 backbone were frozen, while the higher layers remained trainable. In particular, the first 15 layers of the VGG16 model were frozen, allowing the deeper convolutional layers to adapt to high-level, task-specific representations while limiting unnecessary updates to lower-level features.

E. Model Training

The network was trained using the *Sparse Categorical Cross-Entropy* loss function, defined as:

$$L = -\sum_{i=1}^{C} y_i \log(\hat{y}_i), \tag{1}$$

where C denotes the number of classes, y_i represents the ground truth class label, and $\hat{y}_i$ denotes the predicted probability for class i.

The Adam optimization algorithm was employed during training. An initial learning rate of 1×10^{-4} was used in the primary training phase, followed by learning rate adjustments, including 1×10^{-3} and 1×10^{-5}, during subsequent fine-tuning stages to ensure stable convergence. The model was trained with a batch size of 32 for up to 20 epochs per training stage.

To mitigate overfitting and enhance training stability, early stopping and learning rate reduction strategies were applied based on validation loss.

F. Evaluation Protocol

The performance of the proposed model was evaluated using overall classification accuracy, along with class-wise performance analysis. Training and validation accuracy and loss curves were monitored throughout the training process to assess convergence behavior and generalization capability. These evaluation measures provide a comprehensive assessment of the effectiveness of the proposed architecture and training strategy.

V. Experiments

In the initial stage of our experiments, a comparative evaluation was conducted using the EfficientNet [17] and ResNet-18 architectures. Both models achieved high classification accuracy, which can be attributed to their depth and strong representational capacity. However, despite these promising results, the primary objective of this work was to investigate methodological novelty, particularly given that the dataset is relatively small and visually easy to classify. Thus, we intentionally adopted an older architecture and challenged ourselves to develop a functional and competitive model through a careful training design.

As a baseline, a VGG16 model was trained from scratch using randomly initialized weights. Only the convolutional layers of VGG16 were retained, followed by a global average pooling and a lightweight classification head. Due to the depth and large number of parameters of VGG16, this baseline configuration exhibited limited generalization performance when trained on the small dataset. To address these limitations, a series of controlled experiments were conducted using variants of the VGG16 CNN. All experiments were performed under a fixed data preprocessing pipeline and consistent training conditions to ensure fair comparison between models.

To further support these findings, Table II summarizes the training configurations used for each model, including learning rate, number of epochs, and the corresponding accuracy achieved.

TABLE II: Performance of EfficientNet, ResNet-18, baseline VGG16, and proposed VGG16 model

Model	Learning Rate	Epochs	Accuracy (%)
EfficientNet	1e-3	10	96%
ResNet-18	1e-3	10	93%
Baseline VGG16	1e-4	15	73%
Proposed VGG16	1e-3	20	93%

Table II compares the performance of EfficientNet, ResNet-18, a baseline VGG16 trained from scratch, and the proposed refined VGG16 model. EfficientNet and ResNet-18 achieve high classification accuracy (96% and 93%, respectively) within a number of 10 epochs, reflecting the strong representational capacity and efficiency of modern deep architectures. In contrast, the baseline VGG16 model, trained from scratch with randomly initialized weights, attains significantly lower accuracy (73%), highlighting the challenges of training large classical networks without pretrained features, particularly under data-constrained conditions. Through systematic architectural refinement and the introduction of training stabilization techniques, the proposed VGG16 model achieves a substantial improvement, reaching 93% accuracy. This result demonstrates that careful model design and optimization can significantly enhance the performance of classical CNN architecture without relying on pretrained weights, while maintaining controlled and interpretable performance gains.

The details of the experiments performed on the baseline VGG16 are shown in Table III.

TABLE III: Training and performance of baseline VGG16, refined VGG16, and proposed VGG16 models

Model	Head (units)	Pretrained Weights	Accuracy (%)
Baseline VGG16	128	None	73%
Refined VGG16	32	None	91%
Proposed VGG16	256	None	93%

As a baseline, a VGG16 network was trained from scratch using randomly initialized weights. The original fully connected classification layers of VGG16 were removed, retaining only the convolutional feature extractor. A custom classification head consisting of global average pooling, dropout, and fully connected layers was appended to perform the final classification task. All layers were trained end-to-end. This baseline exhibited limited generalization capability, primarily due to the large number of trainable parameters and the absence of pretrained representations, which is particularly challenging for relatively small datasets.

To address the inefficiency observed in the baseline, the classification head was progressively simplified. The refined VGG16 architecture reduced the number of dense units and relied more heavily on global average pooling to aggregate spatial features. This design choice significantly lowered the parameter count while encouraging the model to learn more discriminative convolutional features rather than memorizing training samples. Importantly, these refinements were implemented without introducing pretrained weights, preserving the experimental focus on learning from scratch.

Beyond architectural modifications, additional training stabilization techniques were incorporated to improve convergence behavior, which brings us to our proposed VGG16. Early stopping was employed to prevent overfitting by halting training once validation performance ceased to improve. Furthermore, adaptive learning rate scheduling was used to facilitate smoother optimization and avoid premature convergence. These techniques improved validation accuracy and robustness without altering the core network structure, highlighting the importance of optimization strategy in deep learning experiments [16].

A comparison between our proposed model and the pretrained VGG16 model is shown in Table IV.

TABLE IV: Training and performance of proposed VGG16 and pretrained VGG16

Model	Pretrained Weights	Accuracy (%)
Proposed VGG16	None	93%
Pretrained VGG16	ImageNet	99%

Pretrained weights were intentionally not adopted in the proposed model, despite their ability to achieve high accuracy with rapid convergence as shown in Table IV. Preliminary experiments showed that the use of pretrained VGG16 weights led to large and unstable performance gains that varied significantly with minor changes in training conditions, thereby obscuring the effects of architectural refinement and training stabilization. In contrast, the proposed model trained from scratch exhibits more gradual and consistent learning behavior, allowing the impact of training stabilization techniques to be evaluated in a controlled manner. This approach achieves performance comparable to pretrained configurations while ensuring stable convergence and interpretable performance improvements.

VI. Results

The proposed VGG16 model with architectural refinement and training stabilization achieves a final test accuracy of 93%, demonstrating strong generalization performance without the use of pretrained weights. The model benefits from a lightweight and regularized classification head combined with training stabilization techniques, resulting in improved convergence, reduced overfitting, and consistent validation performance. Training dynamics, as illustrated by the loss and accuracy curves over epochs, show smooth and stable optimization with a minimal generalization.

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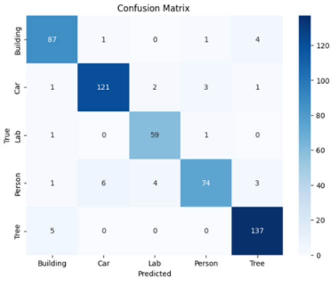

Fig. 3: Confusion matrix of the proposed model on the validation set.

VII. Conclusion

This work presented a systematic refinement of a classical VGG16 architecture trained entirely from scratch for image classification. Starting from a baseline model, architectural improvements were introduced through a lightweight and regularized classification head, followed by the incorporation of training stabilization techniques to enhance convergence and generalization. Experimental results demonstrate that these refinements lead to substantial performance gains, achieving strong classification accuracy, stable training behavior, improved calibration, and balanced class-wise performance without relying on pretrained weights. The findings highlight that careful architectural design and optimization strategy can significantly improve the effectiveness of classical convolutional neural networks in data-constrained settings.

Future work may explore extending the proposed approach to larger datasets or integrating alternative attention mechanisms to further enhance robustness and scalability.

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