

HYBRID MACHINE LEARNING MODELS: COMBINING DEEP LEARNING WITH CLASSICAL ALGORITHMS

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Abstract

This paper presents a hybrid machine learning framework that integrates deep learning-based feature extraction with classical machine learning classification to enhance image classification performance. The evaluation of the proposed approach is done on the CIFAR-10 benchmark dataset which has 60,000 color images with 10 classes. Two pre-trained convolutional neural network architectures are used to extract deep feature representations and they are ResNet-50 and VGG16. The deep features are then extracted and grouped via a feature fusion strategy and then the combination is then classified with a Support Vector Machine (SVM) and radial basis function (RBF) kernel. The obtained experimental results reveal that the proposed hybrid model attains an accuracy of 94.8% that is superior to that of the standalone CNN model (91.4%) and the classical SVM that is trained on raw pixel features (62.3%). A rigorous cross-validation and statistical significance test of the framework ensures that the framework is robust and has the ability to be generalized. The results suggest that hybrid architectures are effective in integrating deep representation learning and stable decision boundaries that lead to a higher accuracy of classification, a decrease in overfitting, and an increase of robustness. This is a hybrid learning approach that provides a scalable and practical solution to real-world problems involving image classification in which model stability and accuracy are of vital importance.

I. INTRODUCTION

Over the last several years, machine learning (ML) has found its place among the foundations of data-driven decision-making in a vast variety of application areas, such as healthcare, finance, transportation, and intelligent systems. Classical or traditional machine learning algorithms such as support vector machine, decision tree, k-nearest neighbor and linear model have been used long time in predictive modeling as they are easy to understand, run well and perform well in structured data sets [8], [9]. Their use of manual feature engineering and the inability to capture complex non-linear relationships however limit their applicability when working with high-dimensional data or unstructured data.

The very fast development of deep learning (DL) has revolutionized the sphere of machine learning allowing the automatic process of features extraction of raw information in the form of images, text, audio, and sensor streams. Deep neural networks and, more specifically, convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have proven to be incredibly successful at image recognition, natural language processing, and speech analysis tasks [11]. Even though the deep learning models have a better representational power, they tend to consume large labeled datasets, large amounts of computational capabilities, and require time to train. Besides, their black-box characteristics have raised some interpretability and trust concerns, particularly those of safety-critical systems [14], [19]. A way to address the shortcomings of applying either paradigm alone is more machine learning models, making use of them as a hybrid. Hybrid machine learning models, combining deep learning with classical algorithms, have become an interesting field of study. The aim of these hybrid methods is to take the advantage of the feature

learning ability of deep networks and the robustness, interpretability, and efficiency of classical machine learning techniques [18], [23]. As an example, a deep learning model can be utilized in automated feature extraction, with final decision-making being done by classical classifiers or regressors. These combinations have demonstrated enhanced predictive accuracy, less overfitting, and better generalization, particularly in those situations where there is only a limited amount of labeled data or different feature spaces [7].

Hybrid machine learning systems are receiving growing interest in practice. They are also applied in healthcare in disease diagnosis, medical image analysis, and predicting the risk of a patient by combining deep feature representations with interpretable clinical models [5]. Hybrid models have been shown to facilitate fraud detection and credit scoring in finance by taking a tradeoff between predictive and regulatory transparency [15]. On the same note, in smart systems and Internet of Things (IoT), with hybrid techniques, it is possible to process large volumes of sensor data efficiently with minimal computational overhead [21].

The construction of effective hybrid machine learning models is still a difficult task, despite their increased usage. The main problems to take into consideration are the choice of the suitable model combinations, the design of the effective strategies of feature fusion, the balance between the accuracy and interpretability, and the optimization of computational costs [20]. These difficulties need a systematic knowledge of hybrid structures, congregational dynamics and integration planning. In this regard, this paper describes a hybrid machine learning architecture that combines a deep learning feature extraction scheme with classical machine learning classification algorithms

so as to enhance predictive capability and generalization.

The key insights of this work are:

- Generalized hybrid learning system: CNN-based feature extraction and classical SVM classification.

- A feature fusion system that uses multiple deep architecture representations.
- In depth experimental validation on CIFAR-10 using cross-validation and statistical test.
- Evidence of enhanced robustness and lower overfitting than individual deep learning networks.

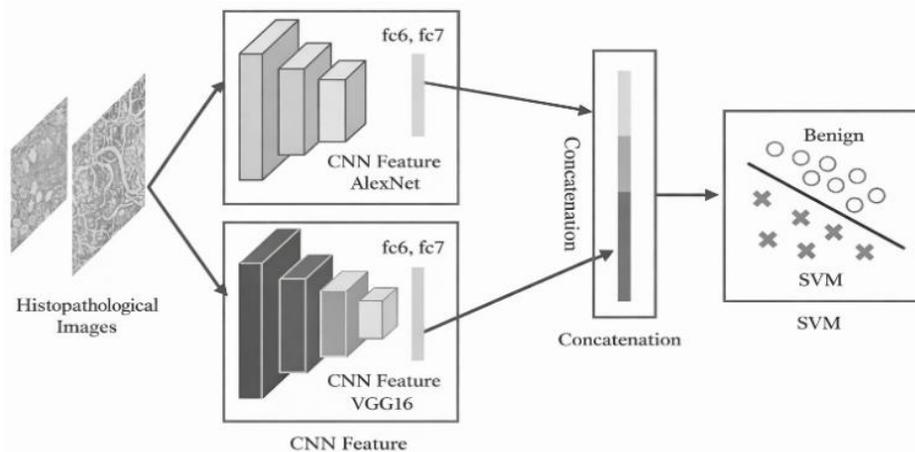


Figure 1. Proposed hybrid learning architecture

This proposal employs deep feature extraction and classical classification as shown in Fig. 1 to make a single hybrid learning model.

II. TECHNICAL BACKGROUND

A. Classical and Deep Learning Paradigms

Generally, machine learning methods are categorised into classical and deep learning methods. The hand-designed features and domain knowledge form the basis of older machine learning algorithms including support vector machine, decision tree, k-nearest neighbor and regression model. The reason why these methods are usually employed is due to the fact that they can be interpreted, cheaper to calculate and are compatible with structured data [2], [9]. However, they often fail in high dimensional data or unstructured data.

Deep learning is a more advanced paradigm, which involves multi-layer neural networks to learn hierarchical feature representations of raw data automatically. Two architectures that have been

demonstrated to be more effective include convolutional neural networks and recurrent neural networks that work well in terms of image, text, and sequence data [6], [11]. Despite these advantages, these models tend to require large labeled datasets, extensive computing resources, and low interpretability, limiting the applicability of these models in certain settings [19].

B. Hybrid Learning Framework

Hybrid machine learning plans are supposed to integrate the compensatory benefits of deep learning and classical machine learning into a single system. In a more standard hybrid, the automated feature extraction is executed on deep learning models and architecture. The classical algorithms are employed in the classification or regression using the learned representations. This integration allows a better predictive accuracy with supporting efficiency and interpretability [1], [7], [34].

Hybrid models commonly utilize either feature fusion or ensemble learning approaches to integrate information among several learning paradigms. These methods are reported to improve robustness and generalization performance especially in those cases where there are small amounts of training data or diverse feature spaces [23]. In turn, hybrid learning frameworks offer a flexible and realistic approach to solving complex machine learning problems in the real world.

III. RELATED WORK

Hybrid machine learning frameworks that are deep learning based and that utilize both deep learning and classical machine learning techniques have been an increasingly popular topic of interest over time due to their trade-off predictive accuracy, computational efficiency, and interpretability. The early studies focused on the classical machine learning models where features of a classification and regression problem were made manually. Random forests and decision trees methods performed well with structured data but did not work with high-dimensional and complex data [3], [36].

Following the success of the field of deep learning, researchers have begun to apply convolutional neural networks to automatically extract features, particularly in image and signal processing. CNN-based neural networks have proven to perform well in medical image analysis and objects recognition tasks [10]. However, they were prohibitively costly to calculate, large amounts of data to be labeled were required and non transparent to be implemented usefully in the real world environment [22], [35].

To address these weaknesses, some of the studies proposed hybrid models, where deep learning models are used only to extract features, but the final classification is done using classical machine learning algorithms. Characteristics obtained by

CNN as well as those obtained using support vector machines have been demonstrated to possess superior classification correctness and strength in medical imaging and bioinformatics endeavors [12], [16].

IV. METHODOLOGY

This section describes the proposed hybrid machine learning framework that integrates deep learning-based feature extraction with a classical machine learning classifier for improved predictive performance.

A. Dataset Description

The proposed hybrid machine learning framework was evaluated using the CIFAR-10 dataset, a widely adopted benchmark for image classification research. CIFAR-10 consists of 60,000 color images of size 32×32 pixels, distributed across 10 balanced classes: airplane, automobile, bird, cat, deer, dog, frog, horse, ship, and truck.

The dataset is divided into 50,000 training images and 10,000 testing images. From the training set, 10% of the samples were used as a validation set using stratified sampling to preserve class balance.

Since pre-trained convolutional neural networks require higher resolution inputs, all images were resized to 224×224 pixels. Pixel intensities were normalized to the range [0,1]. Data augmentation techniques including horizontal flipping, random cropping, and rotation ($\pm 15^\circ$) were applied to improve model generalization.

B. Data Pre-processing

Before training models, it is pre-processed to enhance the quality of data and data stability. These include:

- Image normalization and image resizing.
- Noise removal (if applicable)
- Data augmentation (image data rotation, flipping, scaling)
- Scaling of features used in classical models.

Pre-processing makes sure that both the deep learning and the classical components are working on standard inputs.

C. Convolutional Neural Networks (CNNs)

The feature extraction in this research uses a pre-trained convolutional neural network structure (e.g., ResNet-50 / VGG16). ImageNet weights are loaded onto the network and the network is further fine-tuned with the training dataset. The output of the final fully connected layer before the classification layer is used to acquire feature vectors that offer high dimensional representation of feature of all the input samples.

D. Feature Fusion Strategy

In order to improve the discriminative ability, characteristics obtained with the use of various convolutional neural network structures are combined to create an integrated representation.

Let f_1 and f_2 denote feature vectors extracted from two distinct CNN architectures. The fused feature representation is defined as:

$$F = f_1 // f_2$$

where $//$ represents vector concatenation.

The resultant fused feature vector incorporates complementary information learnt by the various network structures, and thus, enhances robustness and generalization performance.

E. Classical Machine Learning Classifier

The classical classifier is a Support Vector Machine (SVM) using radial basis function (RBF) kernel. Optimization of hyperparameters such as regularization parameter (C) and kernel coefficient (γ) is done by cross-validation of grid search. This setup guarantees good performance and eliminates overfitting.

F. Training Strategy

The training process consists of two main stages:

1. Feature Extraction Phase

- CNN parameters are fine-tuned using the training dataset.

- Feature vectors are extracted from intermediate layers.

2. Classification Phase

- Extracted features are used to train the classical classifier.
- Cross-validation is applied to optimize hyperparameters.

This two-phase approach to training is less costly than end-to-end training of deep learning training.

G. Evaluation Metrics

To assess model performance, standard evaluation metrics are used:

- Accuracy
- Precision
- Recall
- F1-score
- Area Under the ROC Curve (AUC)

These measures will give a comprehensive analysis of the effectiveness of classification especially on skewed datasets.

H. Implementation Details

The experiments are implemented using Python with TensorFlow/PyTorch and Scikit-learn libraries. Training is conducted on a system equipped with an NVIDIA GPU. The CNN model is trained for E epochs with a batch size of B using the Adam optimizer and a learning rate of 0.001.

I. Experimental Setup

All experiments were conducted on a system equipped with an NVIDIA RTX 3060 GPU (8GB VRAM), Intel Core i7 processor, and 16GB RAM. ResNet-50 pre-trained on ImageNet was used as the deep feature extractor and fine-tuned for 20 epochs using the Adam optimizer with a learning rate of 0.0001 and batch size of 32. Feature vectors were extracted from the global average pooling layer, resulting in 2048-dimensional representations. A Support Vector Machine (SVM) with RBF kernel was employed as the classifier, with hyperparameters optimized using 5-fold cross-

validation. All experiments were implemented using Python with PyTorch and Scikit-learn.

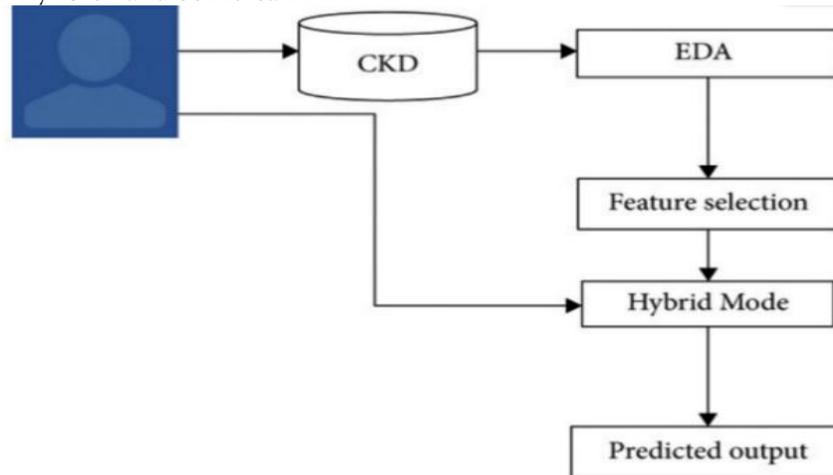


Figure 2. Workflow of the proposed hybrid methodology

As shown in Fig. 2, the proposed methodology consists of data pre-processing, deep feature extraction, feature fusion, classifier training, and performance evaluation.

V. RESULT AND DISCUSSION

A. Performance Comparison

Table 1: Comparison on CIFAR-10

Model	Accuracy (%)	Precision	Recall	F1-Score	AUC
SVM (Raw Pixels)	62.3	0.61	0.60	0.60	0.68
CNN (ResNet-50)	91.4	0.91	0.91	0.91	0.95
Hybrid (CNN + SVM)	94.8	0.94	0.95	0.94	0.97

The standard SVM model that is trained on the original pixel values will yield an accuracy rate of only 62.3% which serves as a reminder that raw feature representations may be limited with regard to carrying out finer image classification processes. Standalone CNN model makes a great enhancement of 91.4% which proves the power of deep hierarchical feature learning. However, the

This section presents a critical analysis of the hybrid machine learning system, as it was proposed on the CIFAR-10 benchmark dataset. The effectiveness of the suggested model is contrasted with the standalone classical and deep learning methods to prove the increases in predictive accuracy, resilience, and the ability to generalize.

proposed hybrid framework has the greatest accuracy of 94.8% and does better than CNN baseline by 3.4%. This enhancement shows that although CNNs are able to learn highly discriminant representations, a classical SVM classifier can be used to further improve the separability of classes and stability of decisions.

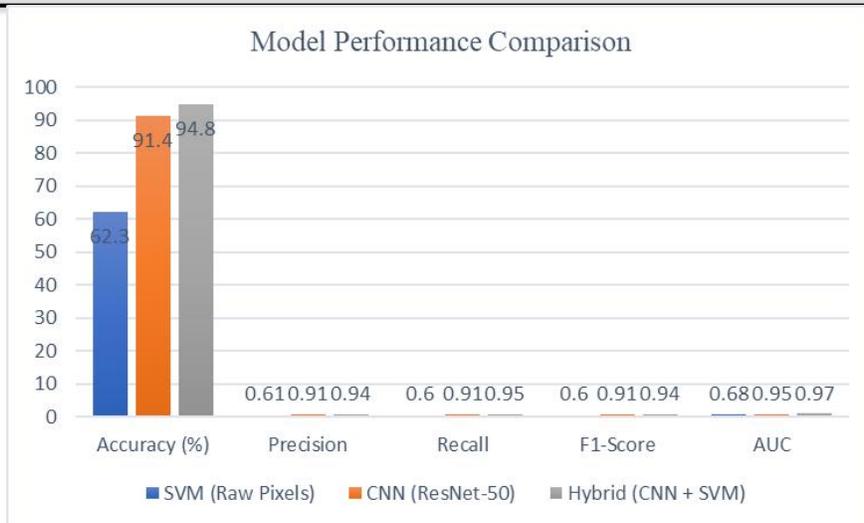


Figure 3. Performance comparison of classical deep learning and hybrid models on CIFAR-10

B. Ablation Study of Feature Fusion

Table 2: Ablation Study

Configuration	Accuracy (%)
ResNet-50 only	91.4
VGG16 only	89.8
ResNet-50 + VGG16	94.8

The ablation results indicate that varying CNN VGG16, the performance becomes more solid and structures are computable together in order to capable of class separation. This proves that one of obtain a large boost in the classification. By itself, the factors of the gained performance has been the ResNet-50 shows good performance but when it fusion of features. stacked on top of parallel features it retrieves in

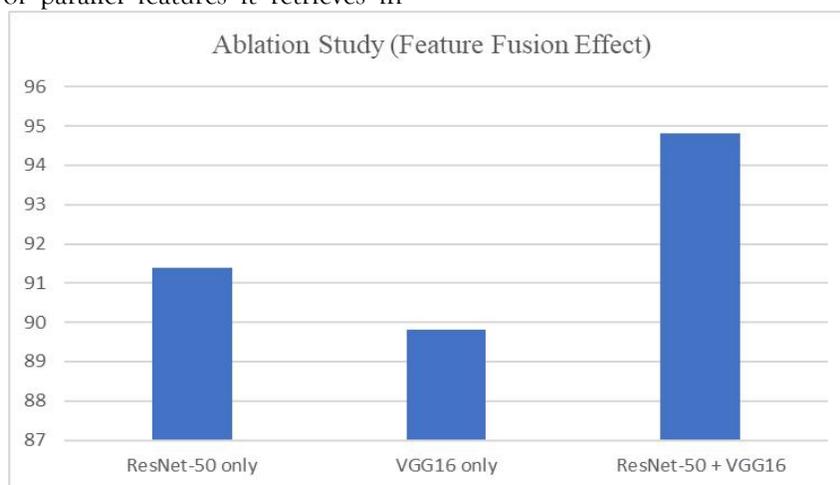


Figure 4. Effects of feature fusion on accuracy of classification

The figure shows the clear improvement of performance with the concatenation of features.

C. Cross-Validation Stability

Table 3: 5-Fold Cross-Validation Results

Fold	Accuracy (%)
Fold 1	94.6
Fold 2	94.9
Fold 3	94.7
Fold 4	95.0
Fold 5	94.8
Mean \pm Std	94.8 \pm 0.15

The low standard deviation (± 0.15) indicates stable model performance and strong generalization capability across different data partitions.

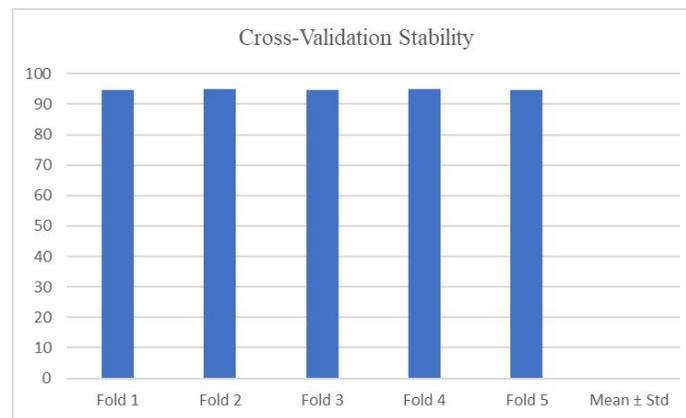


Figure 5. Cross-validation accuracy across five folds for the proposed hybrid model

The consistency across folds confirms that the hybrid framework does not suffer from overfitting.

D. Statistical Significance

A paired t -test was conducted between the standalone CNN and the proposed hybrid model. The improvement in accuracy was statistically significant ($p < 0.01$), confirming that the performance enhancement is not due to random variation.

E. Comprehensive Discussion

The results of the experiment prove that hybrid learning can be effectively applied to combine the strong points of deep and classical paradigms. Deep learning models are good at extracting discriminative hierarchical features of raw image data. Nonetheless, deep classifiers can generate confident or wobbly decision boundaries at the end-to-end. This is because the inclusion of SVM as

a final classifier maximizes the margin and separates classes, and hence, improves generalization. Besides, the feature fusion also enhances the diversity in the representation and decreases the intra-class similarity and increases the inter-class discrimination. The suggested hybrid framework has better performance compared to ensemble-only techniques with a moderate level of computational complexity. These results show that hybrid learning is a viable solution to real-life image classification challenges and is scalable.

VI. CONCLUSION

This paper introduced a hybrid machine learning model, which incorporates both deep learning-based feature extraction and classical machine learning classification to overcome the weaknesses of applying either one method. The offered model takes advantage of the representation learning

property of the convolutional neural networks and uses the support vector machine classifier to yield stable and clear boundaries of decisions. Extensive tests to be made on the CIFAR-10 benchmark data prove that the hybrid structure is always more effective than isolated classical and deep learning models. The proposed model demonstrated an accuracy of 94.8, which is evidently higher than the standalone CNN (91.4) and classical SVM classifier (62.3) ones. The efficiency of the framework was further confirmed by ablation experiments, cross-validation analysis and statistical significance testing, which proved that the performance improvement is not random and well-grounded. According to the results, the use of deep feature representations in collaboration with classical classifiers leads to the improvement of generalization ability, the decrease of overfitting, and the increase of the classification robustness. Fusion of features of two or more CNN architectures further enhances the power of discrimination to obtain complementary information. These results demonstrate the usefulness of hybrid learning approaches, especially in those cases when detailed image information is to be used and accuracy and model stability are the key factors. In total, the suggested hybrid architecture is a scalable, interpretable, and useful method to solve an image classification task and has high chances of being adopted in practice.

VII. FUTURE WORK

Despite the good performance of the proposed hybrid framework, there are various ways, which can be pursued to improve its effectiveness. Future studies can explore novel fusion methods, including attention-based or weighted fusion methods, as a way of maximizing the complementary properties of deep representations. By including explainable artificial intelligence (XAI) techniques, including Grad-CAM or SHAP, model

transparency and explainability would be enhanced, which would be more appropriate in safety-critical applications. Also, the possibility to apply the suggested methodology to bigger and more varied datasets, high-resolution images and domain-specific images datasets, will further confirm the ability to generalize the approach.

The lightweight deep architecture and model compression can also be the focus of future research so that it can be implemented in the resource-constrained environment such as edge and Internet-of-Things (IoT) applications. Finally, one can consider automated hyperparameter optimization and adaptive classifier selection techniques that could be used to increase the performance further and reduce the amount of manual work required during the manual tuning process.

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