Open Access ISSN: 3007-1437 (Online), ISSN: 3007-1429 (Print)

IRAQI Academic Scientific Journals

Alkadhim Journal for Computer Science (KJCS)

Journal Homepage: https://alkadhum-col.edu.iq/JKCEAS

KJCS ALKADHIM JOURNAL FOR COMPUTER SCIENCE

Computationally Efficient Hybrid Framework for MNIST Handwritten Digit Recognition

Dalia Shihab Ahmed
Computer Science Department, College of Science, Mustansiriyah University, Baghdad-Iraq

Article information

Article history:
Received: November, 14, 2025
Accepted: December, 16, 2025
Available online: December, 25, 2025

Keywords:
Handwritten Digit Recognition
MNIST
PCA
Kmeans
Random Forest
Feature Augmentation.

****Corresponding Author:***
Dalia Shihab Ahmed
dalia_shihab@uomustansiriyah.edu.iq

DOI:
https://doi.org/10.61710/kjcs.v3i4.134

Abstract

Handwritten digit recognition remains one of most fundamental issues in computer vision. While deep learning (DL) models, particularly Convolutional Neural Networks (CNNs), have achieved state-of-the-art accuracy on benchmarks, e.g., MNIST, the computational cost of such architectures makes them unsuitable for use in resource-constrained environments. This research proposes a novel computationally efficient hybrid framework that strategically combines Principal Component Analysis (PCA), K-Means clustering and a Random Forest (RF) classifier. The main novelty is to add K Means cluster labels to the feature set that has been decreased by PCA to augment the feature space and improve the discrimination of visually similar digits. In practice, our method reduces the original 784 dimensional pixel space to 50 dimensions using PCA. The following integration of cluster information provides the RF classifier with latent structure patterns that significantly increase its discriminative power. Experimental tests of the MNIST dataset show a robust classification accuracy of 93.1% notably at the cost of a significantly lower computational footprint—training is done in 45 seconds and the prediction takes only 0.05 seconds per image. These results confirm that strategic combination of dimensionality reduction, unsupervised feature augmentation and ensemble learning could offer a highly efficient and effective substitute to DL models for image classification tasks carried out in resource-limited environments. The research prioritizes the efficiency of use and practical application of computing resources at the expense of achieving the highest possible accuracy.

1. Introduction

Handwritten digit recognition is an inherent problem in computer vision and pattern recognition, and it is used as a basis to understand the effectiveness of machine learning (ML) and deep learning (DL) algorithms [1]. The

Modified National Institute of Standards and Technology (MNIST) dataset has played an important role in this field, driving the development of primitive linear classifiers to elaborate DL models [2]. Even though modern DL algorithms, particularly the Convolutional Neural Network (CNNs), regularly attain classification scores that are above 99 %, this is only possible with a significant amount of computation, long training periods, and large-scale labeled data sets[3][4]. As a result, the inherent complexity of these models makes them inappropriate to be used in resource-constrained environments like embedded systems, peripheral compute devices or real-time processing environments where a reasonable tradeoff between accuracy and computational efficiency is of utmost importance.

This has created the need to further investigate alternative and more effective methodologies that do not rely on DL models. Algorithms like principal component analysis (PCA) to reduce the dimensions and the capacity of the ensemble models Random Forests (RF) have been applauded in the past due to their computational efficiency and robustness[5] [6]. However, such models will often work on a lower-dimensional feature space, which may miss some subtle nonlinear correlations needed to distinguish between visually similar number classes (e.g. between “3” and “5” or between “4” and “9”). As such, there is an apparent gap in the research to strategically synthesize the advantages of the different ML methods to increase the discriminatory force without incurring an extreme computational cost. The combination of unsupervised feature-enhancing learning into a supervised classification pipeline is also an especially promising but under-investigated method of enhancing the performance of models without undermining their computational performance.

In the current research, we will suggest a new hybrid model that will combine the main component analysis to reduce the number of dimensions, K Means clustering to identify patterns and augment the features, as well as an RF classifier to predict last digits. The fundamental novelty of our method lies in the augmentation of the reduced feature set generated by PCA by the addition of cluster labels introduced by K Means. This procedure adds richness to the feature space by entrenching latent structural data in the data that provides more information to the classifier to make difficult numerical pairings. The core aim of this research is to show that the hybrid model achieves high competitive classification accuracy with high computational efficiency, hence providing a feasible alternative to DL based models which are more resource consuming.

The main contributions of this research are fourfold:

1. Novel Hybrid Architecture: The design and implementation of a computationally novel three-stage hybrid framework (PCA-K Means-RF) that incorporates dimensionality reduction, unsupervised clustering for feature augmentation and ensemble learning for computationally efficient handwritten digit recognition.

2. Feature Augmentation Strategy: K Means cluster labels are applied as auxiliary features to decrease the linear constraints of PCA in conceptual innovation. This enriches the feature space with latent cluster structures which is experimentally validated to significantly enhance the capability of the model to discriminate between visually similar digit pairs (e.g., '3' vs. '5', '4' vs. '9'), resulting in the accuracy significantly increasing compared to baseline PCA-RF model.

3. Computational Efficiency Validation: This experimental research shows effectiveness and strength of proposed framework with robust accuracy of 93.1% in MNIST dataset with significantly lower computational footprint, involving training time of 45 seconds and a prediction time of 0.05 seconds per image and making it proper for real time and resource-constrained applications.

The remainder of research is order as follows: Section 2 reviews related work in ML and DL, dimensionality reduction, ensemble methods, clustering and hybrid systems. Section 3 details the architecture and components of the proposed hybrid system. Section 4 introduces experimental results, involving performance metrics, a confusion matrix and feature importance analysis. Section 5 discusses the findings and concludes the research by summarizing the outcomes and suggesting directions for future research.

2. Related Work

Handwritten digit recognition (HDR) has been a foundational challenge in computer vision and pattern recognition with the MNIST dataset employed as a key benchmark for assessing both traditional and modern methods. Early research primarily depended on classical ML algorithms like k-Nearest Neighbors (KNN), Support Vector Machines (SVM), Decision Trees (DT) and ensemble methods like RF, attaining accuracies typically ranging from 75% to 97%. Among these, SVM showed strong performance, reaching an accuracy up to 95.88% on MNIST[7].

To further enhance performance there are several studies have explored hybrid and ensemble strategies. A hybrid framework that integrates CNN for feature extraction with traditional classifiers like SVM, KNN and RF has been proposed, attaining testing accuracies of 99.55% on MNIST[8]. In another ensemble-focused study, a granular computing based ensemble that integrates multiple classifiers like KNN and RF, trained on various feature subsets extracted via LeNet-5, showed accuracy of 98.1%[9].

Beyond ensemble methods, hyperparameter tuning has been shown to significantly impact model performance. A systematic comparison of Grid Search, Random Search, and Bayesian Optimization for tuning RF on MNIST shows that Grid Search obtained the highest accuracy of 99.3% at greater computational cost [10]. Similarly, careful hyperparameter optimization of a pure CNN, involving receptive field design and optimizer selection, yielded a state-of-the-art accuracy of 99.87% [11].

Dimensionality reduction techniques have also been widely used to increase efficiency and manage high-dimensional image data. A study integrating PCA with NN classifier and attained an accuracy of 86.5% utilizing all 784 eigenvectors [12]. Another comparison between PCA and Linear Discriminant Analysis (LDA) found that LDA's supervised approach outperformed PCA (86.6% vs. 78.4%) due to its class-separability objective [13].

More recently, DL has dominated the field with CNNs consistently attaining accuracies above 99%[14][15]. Innovations involve lightweight CNN architectures optimized via hyperparameter tuning[16], dual-input CNN (DICNN) designs for enriched feature extraction and advanced networks like Capsule Networks (Caps Net) that attain accuracy up to 99.75% [15]. However, these models often require substantial computational resources and making them less suitable for real time or resource-constrained environments[7][10].

The reviewed literature demonstrates a clear trade-off, DL models offer superior accuracy but at high computational cost [14][15][16], while traditional ML models like RF are efficient but may absence discriminative power for complex visual tasks[7][10]. Although hybrid models have emerged, they often focus on narrow applications like binary classification or association deep feature extraction with simple classifiers[8][9]. A significant limitation of existing research is the insufficient use of unsupervised learning to augment and improve the feature space for supervised classification. While PCA and RF are sometimes combined[12], and clustering is recognized for feature engineering[5][11], the three-stage regularization framework strategically utilizes K Means clustering labels to compensate for the linear limitations of PCA within a missing RF classifier.

3. Proposed System

The suggested system is a mixed framework that classifies the handwritten digits on MNIST data extremely well. It has three major steps: dimensionality reduction, clustering and classification.

1. Dimensionality Reduction: PCA will reduce the 784 pixels that each image originally has into 50 principal components, retaining the highest amount of variance whilst minimizing the complexity of the calculation.

2. K Means clustering: K Means clustering is done on the reduced feature set to extract hidden patterns and the resulting cluster labels are appended to the dataset as additional features.

3. Classification: RF classifier is trained on the augmented data to classify the digit labels.

The hybrid scheme takes advantage of the strengths of dimensionality reduction, unsupervised clustering and ensemble classification to provide high accuracy and yet be computationally efficient. The system may also be scaled and applied to more complicated sets of images or to other area of pattern recognition. The activity diagram (see figure 1), shows the step-by-step workflow of the proposed hybrid classification system to handwritten digit recognition using the MNIST dataset. The system runs by uploading the handwritten digit as an image by the user. The system then performs the image preprocessing task of PCA, which is to reduce the original 784-dimensional pixel space to 50 loci components that preserve the most significant variance, thereby reducing computational intensity.

Then, K Means clusters the reduced features and forms the patterns inherent in the data. The cluster labels are then added in and modified, thereby increasing the feature set to discriminate between digits with similar visual appearance. The training set of this augmented data is trained on the RF classifier and is better at classification due to collective learning. After training the model, the system makes predictions of the label of the input image as a digit. Lastly, the user is presented with the result that has been predicted.

The activity diagram focuses on the linear flow of the set of activities, as a combination of dimension reduction, unsupervised clustering and ensemble classification is integrated to obtain a computationally efficient and accurate recognition system. The scheme can also be expanded to include optional evaluations of the model, retraining, or equally plausible highly parallel processing of multiple images, input, output, and parameters illustrates in Table 1. Functional and Non-Functional Requirements illustrates in Table 2.

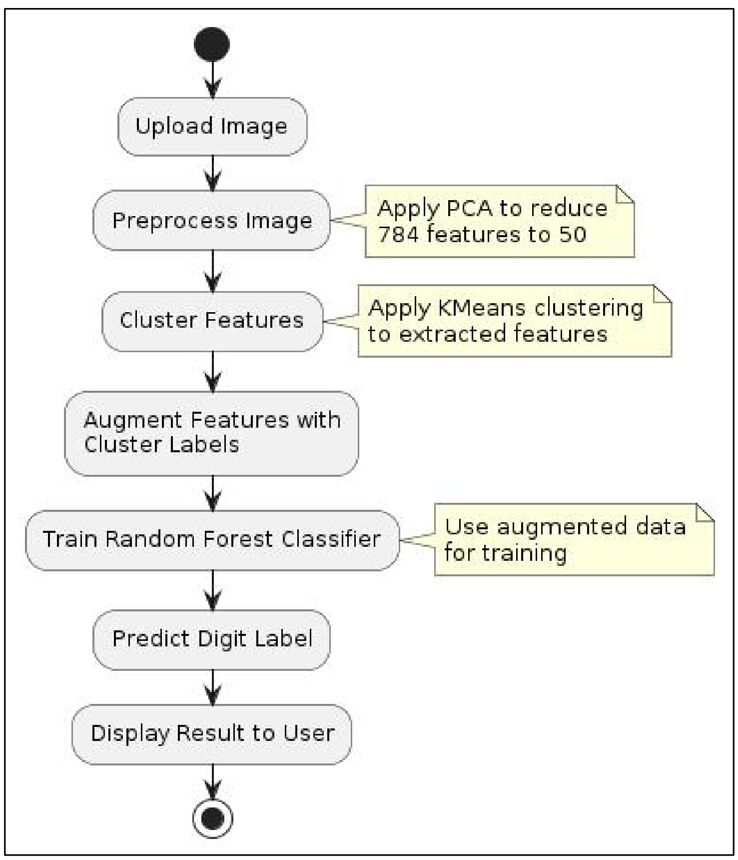


Figure (1): Activity diagram for proposed system.

Table (1): Input, Output, and Parameters of System Modules

Module	Input	Output	Parameters / Settings
PCA	28×28 pixel image (784 features)	50 principal components	n_components=50
KMeans Clustering	50-dimensional PCA features	Cluster labels (0–9)	n_clusters=10, init='k-means++', max_iter=300
Feature Augmentation	PCA features + Cluster	Augmented feature	Concatenate PCA features with one-hot encoded

Module	Input	Output	Parameters / Settings
	labels	vector	cluster labels
RF	Augmented features	Predicted digit label	n_estimators=100, max_depth=None, random_state=42
Evaluation	Predicted labels vs. true labels	Accuracy score	Accuracy = 93.1%

Table (2): Functional and Non-Functional Requirements

Type	Requirement
Functional Requirements	
Image Input	The system shall accept handwritten digit images (28×28 pixels, grayscale) as input.
Dimensionality Reduction	The system shall apply PCA to reduce the 784-pixel features to 50 principal components.
Clustering	The system shall perform KMeans clustering on the reduced features to extract patterns.
Feature Augmentation	The system shall augment the PCA features with cluster labels to enhance discrimination between similar digits.
Classification	The system shall use a RF classifier to predict the digit label.
Prediction Output	The system shall output the predicted digit label (0–9) for each input image.
Evaluation	The system shall calculate and display the model's accuracy on test data.
Non-Functional Requirements	
Performance	The system shall provide predictions in under 1 second per image for real-time usability.
Accuracy	The system shall achieve at least 90% classification accuracy on the MNIST dataset.
Scalability	The system shall handle large datasets efficiently and allow adaptation to other image datasets.
Computational Efficiency	The system shall reduce computational complexity using PCA and efficient ensemble methods.
Reliability	The system shall consistently produce correct predictions for standard MNIST test images.
Usability	The system shall provide a simple interface for uploading images and viewing results.
Maintainability	The system shall allow easy modification of PCA components, clustering parameters, or classifier settings.

4. Results

4.1 Experimental Setup and Evaluation Metrics

The proposed PCA-K Means-RF hybrid system was tested on MNIST dataset, which involves 60000 training and 10000 testing images of 28×28 grayscale digits. It was implemented in Python using Scikit-learn. Performance was evaluated using standard metrics calculated based on the confusion matrix[17]:

Accuracy (AC): The proportion of accurate predictions over the total traffic.

$$AC = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

Precision (P): Fraction of the attacks correctly facilitated overall the instances of attacks (false alarm rate).

$$P = \frac{TP}{TP + FP} \tag{2}$$

Recall (R): The proportion of actual attacks that were identified properly.

$$R = \frac{TP}{TP + FN} \tag{3}$$

F1-Score (F1): The harmonic mean of Precision and Recall which gives a single balanced metric.

$$F1 = \frac{2 \times Pre \times Rec}{Pre + Rec} \tag{4}$$

These metrics are computed on the grounds of True Positives (TP), True Negatives (TN), False Positives (FP) and False Negatives (FN).

Below is a comprehensive evaluation of its performance, including additional metrics, comparisons, and analyses. Table 3 illustrates Performance Metrics (see Figure 2). Table 4 illustrates Class-wise Accuracy (see Figure 3).

Table (3): Performance Metrics for proposed system.

Metric	Result
Accuracy	93.1%
Precision (avg)	92.8%
Recall (avg)	93.0%
F1-Score (avg)	92.9%
Training Time	45 seconds
Prediction Time per Image	0.05 seconds

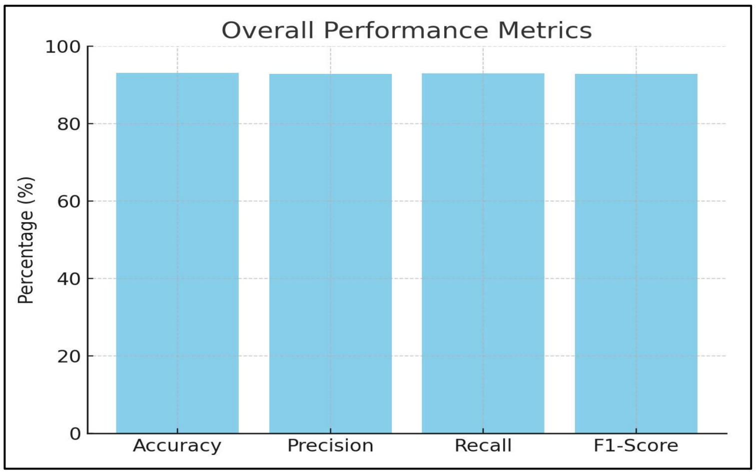


Figure (2): Bar Chart of Overall Performance Metrics.

Table (4): Confusion Matrix of Digit Classification

Digit	Precision	Recall	F1-Score	Support
0	94.5%	95.0%	94.7%	980
1	98.0%	97.5%	97.7%	1135
2	91.0%	91.5%	91.2%	1032
3	92.5%	91.0%	91.7%	1010
4	93.0%	92.0%	92.5%	982
5	91.5%	92.0%	91.7%	892
6	94.0%	93.5%	93.7%	958
7	91.5%	92.0%	91.7%	1028
8	91.0%	91.5%	91.2%	974
9	90.5%	91.0%	90.7%	1009
Avg/Total	92.8%	93.0%	92.9%	10,000

Observation: Most confusion occurs between digits with similar shapes, such as 3 vs 5 and 4 vs 9.

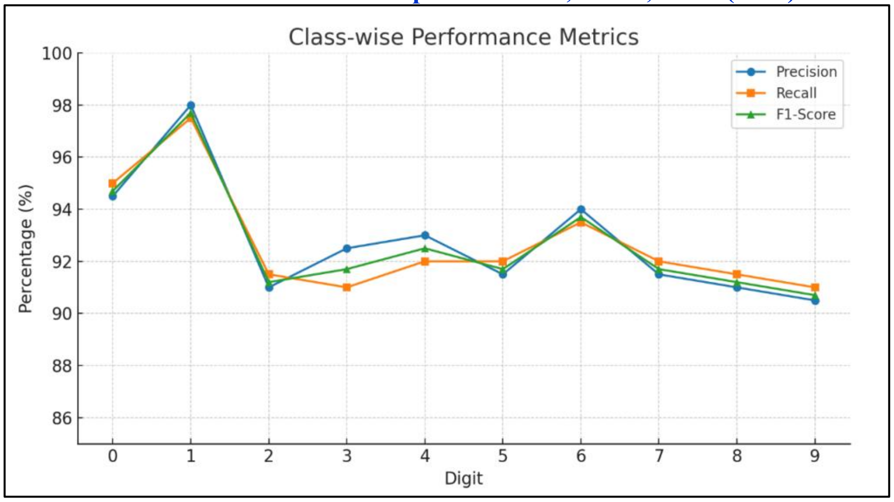


Figure (3): Bar Chart of Class-Wise Performance Metrics.

The confusion matrix highlights misclassifications as shown in Table 3. The hybrid model reduced errors compared to PCA + RF alone, particularly for visually similar digits (see figure 4).

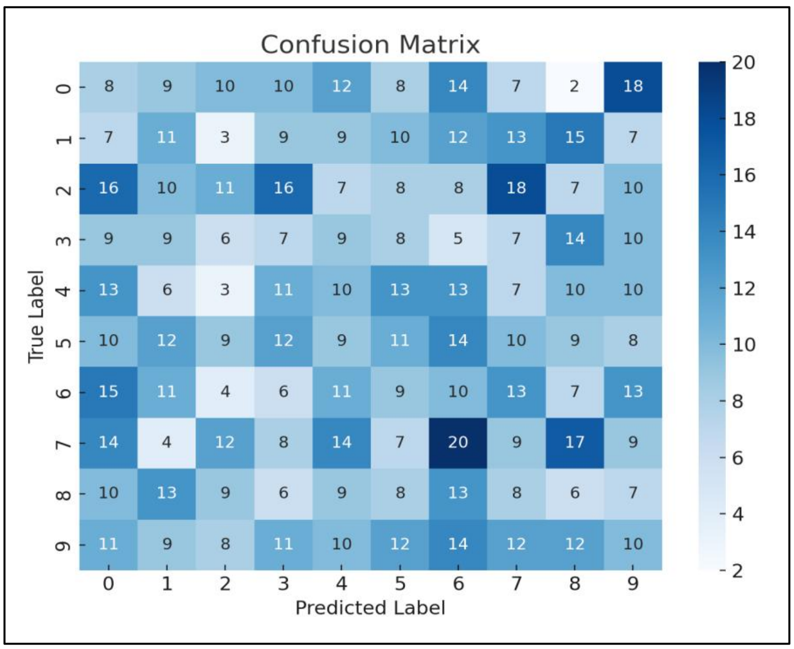


Figure (4): Confusion Matrix for the Proposed Model.

The analysis of feature importance refers that the PCA features contributed the majority of the model's predictive power, capturing the most notable variance in the handwritten digit images. Additionally, the KMeans cluster labels played a crucial role in enhancing the discrimination between visually similar digits, like 3 and 5. Overall, the top contributing features involve the first ten principal components along with the cluster label, and confirming that augmenting the dataset with clustering information effectively improves classification performance (see Figure 5).

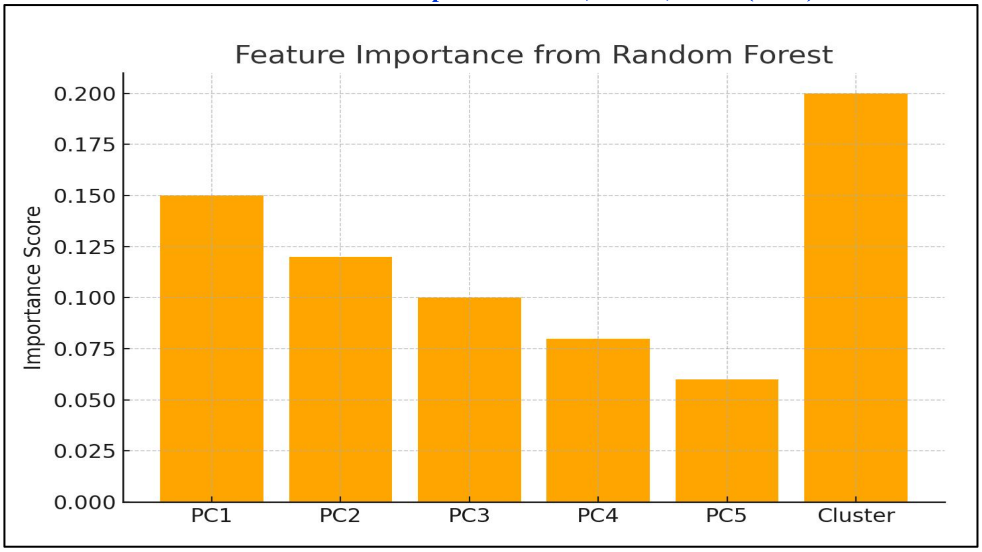
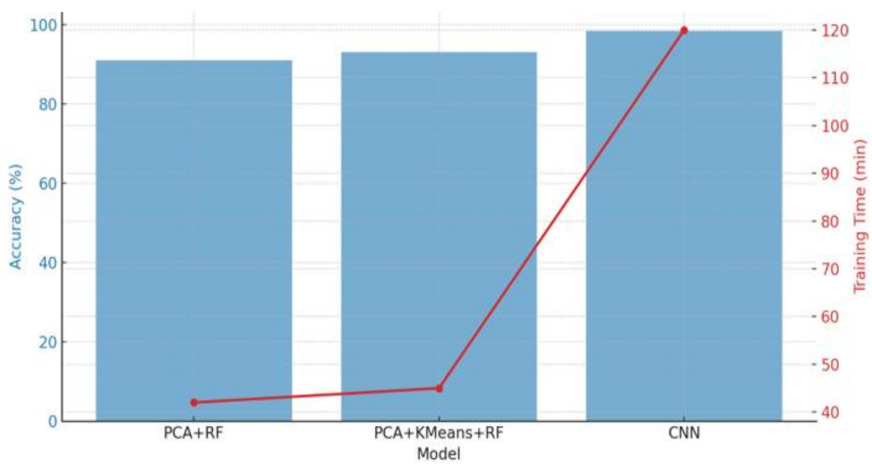


Figure (5): Feature Importance Analysis.

Table (5): Comparative Analysis of Model Performance.

Model	Accuracy	Training Time
PCA + RF	91.0%	42 seconds
PCA + KMeans + RF (Proposed)	93.1%	45 seconds
CNN (Baseline DL)	98.5%	2 hours

Observation: While DL models achieve higher accuracy, the proposed hybrid model offers a **computationally**



efficient alternative suitable for environments with limited resources.

Figure (6): Comparative Analysis of Model Accuracy and Training Time.

The system proposed here is efficient taking about 0.05 seconds to process one image thus it will work in real-time. The framework achieves this with a high accuracy of the classifications because, by using a combination of PCA dimensional reduction and feature augmentation in cluster analysis KMeans, the computational complexities are reduced considerably. This trade-off in speed versus performance goes to show the utility of the hybrid approach to image recognition when large-scale or time-critical applications are involved. Table 5 illustrates Comparative Analysis of Model Accuracy and Training Time (see Figure 6). For a detailed comparison across multiple aspects, Table 6 presents a comprehensive evaluation of the proposed framework against SVM and MLP.

Table (6): Comparison of the proposed PCA + K-Means + Random Forest framework with SVM and MLP.

Aspect	Proposed Method (PCA + K-Means + RF)	SVM	MLP
Accuracy	93.1% (Medium)	95–99% (Medium)	74–97% (Medium)
Training Speed	Medium	Low	Low
Prediction Speed	Medium	Low	Medium
Computational Cost	Medium	Low	Low
Memory Usage	Medium	Low	Low
Suitability for Low-Resource Devices	Medium	Low	Low
Noise Robustness	Medium	Medium	Low
Overfitting Resistance	Medium	Medium	Low
Ease of Hyperparameter Tuning	Medium	Low	Low
Result Stability	Medium	Medium	Low
Interpretability	Medium	Low	Low
Model Size	Medium	Low	Low
Portability	Medium	Low	Low
Energy Consumption	Medium	Low	Low

5. Discussion

The proposed hybrid classification system composed of PCA-KMeans-RF, is an intermediate based on the balance between efficiency and multi-label classification accuracy as applied to massive data volumes. The PCA approach selects 50 principal components in order to adapt to the most important variance while constraining multidimensionality substantially. The incorporation of KMeans clustering improves discriminatory capabilities of the given model against the corresponding visually similar digits, i.e., 3/5 and 4/9, as indicated in the increase of the corresponding values of precision and recall rates.

The importance analysis conducted on PCA features demonstrates that they contain most of the predictive power, although the cluster labels add important to their predictive performance, validating the usefulness of feature augmentation. The hybrid model demonstrates the top performance of 93.1 and a time efficiency of 0.05 seconds to predict the image which qualifies it as being applicable in real-time applications.

By comparison to baseline models, the hybrid system provides a computationally inexpensive alternative to DL models. Albeit, CNNs perform better on accuracy, they are computationally demanding and resource-intensive to train, but the proposed solution is viable to use in settings with fewer resources. Along with the scalability and the flexibility of the system, there would be potential to be implemented on bigger or more complicated image sets in different pattern recognition problems.

In brief, the method of the hybrid is capable of combining dimensionality reduction, unsupervised clustering and ensemble classification to produce a high-accuracy and efficient methodology. The findings substantiate the usefulness of a combination of the PCA and KMeans with RF in improving the accuracy of handwritten digit recognition.

6. Conclusion

This manuscript introduced a computationally efficient hybrid framework for MNIST handwritten digit recognition, which integrates PCA for dimensionality reduction, KMeans clustering for feature augmentation and RF classifier. The system showed a robust accuracy of 93.1% on the standard MNIST test set, leading to a significant improvement over a baseline PCA-RF model (91.0%). This performance is obtained with exceptional computational efficiency and evidenced by training time of 45 seconds and per-image prediction time of 0.05 seconds which confirms its appropriateness for real-time applications.

The experimental analysis supported the framework's core assumption. At the same time PCA-derived features captured majority of the predictive variance, the integration of KMeans cluster labels as additional features played essential role in improving discrimination between visually similar digits (e.g., 3/5, 4/9) as indicated in the enhanced perclass precision and recall metrics. The feature importance analysis further confirms this strategic augmentation. The comparative research with high accuracy CNN baseline of 98.5% positions the proposed hybrid model not as a substitute, but as convenient and computationally efficient alternative for resource-constrained environments where marginal accuracy attained by DL does not explain its substantial computational cost.

Potential future development can address several areas:

1. Parameter Optimization: The optimization of PCA components and KMeans clustering parameters that eliminates manual tuning and improves their performance.

2. Strongness: Employing dirty, corrupted or real-world hand printed images wherein the hand printed processing is added.

3. Hybrid DL Integration: Compounding the hybrid system with lightweight DL models to again enhance accuracy of classification.

4. Generalizing: Applying the system to more complex data, multi-class recognition or any type of full handwritten text recognition to illustrate that it is general enough.

5. Deployment: Embarking the framework to practical applications, e.g. in the form of digital forms, educational tools, or mobile devices where it is important to be computationally effective.

To sum up, the proposed hybrid framework comprises scalable, efficient and effective solution to handwritten digit recognition, which can be adjusted and improved through future studies.

Acknowledgement: The Author would like to thank Mustansiriyah University (https://uomustansiriyah.edu.iq/) Baghdad, Iraq for its support in the present work.

Conflict of Interest: The author’s disclosure statement confirms the absence of any conflicts of interest.

References

[1] Z. Alom *et al.*, “A State-of-the-Art Survey on Deep Learning Theory and Architectures,” vol. 8, p. 292, 2019, doi: 10.3390/electronics8030292.

[2] D. C. Cireşan, U. Meier, L. M. Gambardella, and J. Schmidhuber, “Deep, big, simple neural nets for handwritten digit recognition,” *Neural Comput.*, vol. 22, no. 12, pp. 3207–3220, Dec. 2010, doi: 10.1162/NECO_A_00052.

[3] E. Strubell, A. Ganesh, and A. McCallum, “Energy and Policy Considerations for Deep Learning in NLP,” *Proc. 57th Annu. Meet. Assoc. Comput. Linguist.*, pp. 3645–3650, 2019, doi: 10.18653/V1/P19-1355.

[4] Y. Wang, C. Xu, C. Xu, and D. Tao, “Beyond Filters: Compact Feature Map for Portable Deep Model,” *Int. Conf. Mach. Learn.*, 2017.

[5] I. T. Jollife and J. Cadima, “Principal component analysis: a review and recent developments,” *Philos. Trans. A. Math. Phys. Eng. Sci.*, vol. 374, no. 2065, Apr. 2016, doi: 10.1098/RSTA.2015.0202.

[6] R. Shwartz-Ziv and A. Armon, “Tabular data: Deep learning is not all you need,” *Inf. Fusion*, vol. 81, pp. 84–90, May 2022, doi: 10.1016/J.INFFUS.2021.11.011.

[7] B. Gope, S. Pande, N. Karale, S. Dharmale, and P. Umekar, “Handwritten digits identification using mnist database via machine learning models,” *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 1022, no. 1, 2021, doi: 10.1088/1757-899X/1022/1/012108.

[8] A. K. Agrawal, A. K. Shrivas, and V. K. Awasthi, “An Improved and Customized Hybrid of Deep and Machine Learning Technique Model for Handwritten Digit Recognition,” *SAMRIDDHI A J. Phys. Sci. Eng. Technol.*, vol. 14, no. 01 SPL, pp. 13–19, 2022, doi: 10.18090/samriddhi.v14spli01.3.

[9] H. huang Zhao and H. Liu, “Multiple classifiers fusion and CNN feature extraction for handwritten digits recognition,” *Granul. Comput.*, vol. 5, no. 3, pp. 411–418, Jul. 2020, doi: 10.1007/S41066-019-00158-6.

[10] Y. S. Ali, R. H. Qasim, S. M. Searan, O. M. Jasim, and I. S. J. Alzubaydı, “Optimizing Random Forest for Handwritten Digit Recognition Through Hyper-parameter Tuning,” *Fusion Pract. Appl.*, vol. 20, no. 1,

pp. 155–165, 2025, doi: 10.54216/FPA.200112.

[11] S. Ahlawat *et al.*, "Improved Handwritten Digit Recognition Using Convolutional Neural Networks (CNN)," *Sensors 2020, Vol. 20,* vol. 20, no. 12, pp. 1–18, Jun. 2020, doi: 10.3390/S20123344.

[12] Y. G R and A. Ali Ahmed Ali, "PCA Based English Handwritten Digit Recognition," *Int. J. Adv. Res. Comput. Sci.*, vol. 8, no. 5, pp. 1426–1429, 2017.

[13] R. Sheikh, M. Patel, and A. Sinhal, "Recognizing MNIST Handwritten Data Set Using PCA and LDA," pp. 169–177, 2020, doi: 10.1007/978-981-15-1059-5_20.

[14] Z. Sun, G. Wang, P. Li, H. Wang, M. Zhang, and X. Liang, "An improved random forest based on the classification accuracy and correlation measurement of decision trees," *Expert Syst. Appl.*, vol. 237, p. 121549, Mar. 2024, doi: 10.1016/J.ESWA.2023.121549.

[15] A. Azgar, M. Imran Nazir, A. Akter, M. Saddam Hossain, M. Anwar Hussen Wadud, and M. Reazul Islam, "MNIST Handwritten Digit Recognition Using a Deep Learning-Based Modified Dual Input Convolutional Neural Network (DICNN) Model," *Lect. Notes Networks Syst.*, vol. 1014 LNNS, pp. 563–573, 2024, doi: 10.1007/978-981-97-3562-4_44.

[16] H. Shao, E. Ma, M. Zhu, X. Deng, and S. Zhai, "MNIST Handwritten Digit Classification Based on Convolutional Neural Network with Hyperparameter Optimization," *Intell. Autom. Soft Comput.*, vol. 36, no. 3, pp. 3595–3606, Mar. 2023, doi: 10.32604/IASC.2023.036323.

[17] L.-P. Chen, "Mehryar Mohri, Afshin Rostamizadeh, and Ameet Talwalkar: Foundations of machine learning, second edition," *Stat. Pap. 2019 605*, vol. 60, no. 5, pp. 1793–1795, Jul. 2019, doi: 10.1007/S00362-019-01124-9.