BALKAN JOURNAL OF ELECTRICAL & COMPUTER ENGINEERING, Vol. 14, 2026
Research Article

Hybrid CNN–ML System for Wind Speed Level Identification in Complex Terrain: A Case Study from Maden, Turkey

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Abstract—**This study proposes a hybrid deep and traditional learning framework for wind speed level classification in the complex terrain of the Maden region, Turkey. A one-dimensional convolutional neural network (1D-CNN) was employed for automatic feature extraction from a 30-day meteorological window, followed by classification using multiple machine learning algorithms. Among them, K-Nearest Neighbor (KNN) achieved the highest accuracy (98.75%) when applied to features extracted from the global average pooling (GAP) layer. The hybrid CNN–KNN model significantly outperformed standalone CNN and KNN baselines. The study highlights the effectiveness of combining deep feature representations with interpretable classifiers in data-scarce, topographically challenging regions, offering a transparent and high-performance alternative for wind energy assessment.**

Index Terms— **Feature-based categorization, complex terrain, renewable energy planning, wind speed classification**

I. INTRODUCTION

Wind energy plays a pivotal role in the global transition toward clean and sustainable energy systems [1]. Accurate classification of wind speed is essential for resource assessment, site selection, and the efficient integration of wind energy into regional power networks. Traditionally, statistical models such as Weibull or Rayleigh distributions have been used to estimate wind behavior; however, these models often fall short when dealing with nonlinear, complex, and region-specific meteorological variations [2].

Recent advances in data-driven methods have introduced machine learning approaches as more flexible and accurate alternatives for analyzing wind speed data. These models have demonstrated strong performance in handling high-dimensional datasets and can adapt to diverse terrains and climatic conditions. Nevertheless, many existing studies focus on offshore or flatland environments, where wind flow patterns are relatively predictable. In contrast, mountainous or complex terrains, like the Maden region of Turkey, present unique challenges due to abrupt elevation changes and microclimatic variability. The Maden region is characterized by complex and rugged terrain, as illustrated in Figures 1–3. This complexity significantly affects wind speed patterns and presents challenges for accurate forecasting.

To address these challenges, this study aims to develop a high-fidelity wind speed classification framework specifically tailored to the Maden region's rugged topography and complex atmospheric conditions, where abrupt elevation changes and heterogeneous surface roughness significantly affect wind behavior. As illustrated in Figure 1, the elevation map derived from DEM data shows steep elevation gradients across the area. Figure 2 further quantifies this complexity by depicting surface roughness values computed from elevation gradients, highlighting areas of high turbulence potential. To provide an intuitive understanding of this terrain-induced variability, a 3D topographic visualization is presented in Figure 3, clearly revealing the uneven landscape and its potential impact on wind flow. Collectively, these visualizations underscore the inadequacy of flatland-based modeling assumptions and highlight the necessity for a terrain-aware, high-resolution classification framework tailored to the region's rugged characteristics. Therefore, the proposed framework explicitly accounts for this complexity by integrating deep learning with terrain-informed meteorological features for robust wind speed classification [3].

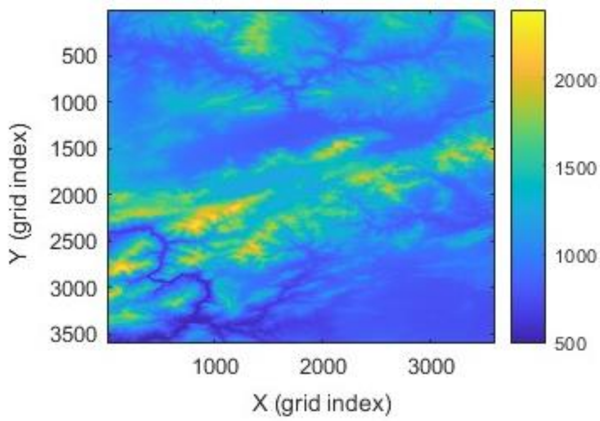

Fig.1. Elevation map of the Maden region derived from DEM data.

While previous studies have shown the effectiveness of both deep learning and traditional classifiers in wind-related tasks, the combination of CNN-based feature extraction with lightweight classifiers remains underexplored in complex

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Manuscript received Nov 09, 2025; accepted Nov 24, 2025. DOI: 10.17694/bajece.1820323

 ISSN: 2147-284X https://dergipark.org.tr/en/pub/bajece

terrains. This study addresses that gap by developing a hybrid CNN–KNN framework tailored to the mountainous Maden region. By comparing standalone KNN, standalone CNN, and the proposed hybrid approach, the research demonstrates that the integration of GAP-extracted features into KNN not only improves accuracy but also provides a scalable and interpretable solution for regional wind classification problems.

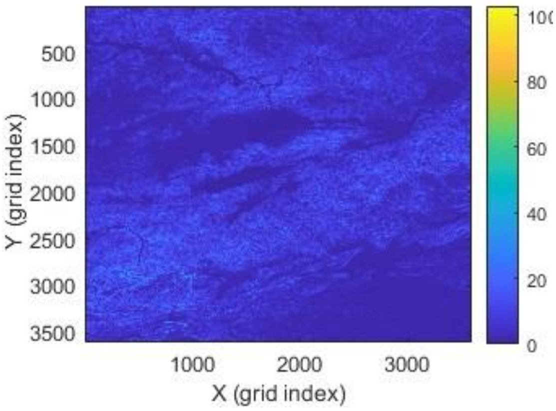

Fig.2. Surface roughness map of the Maden region computed from DEM elevation gradients..

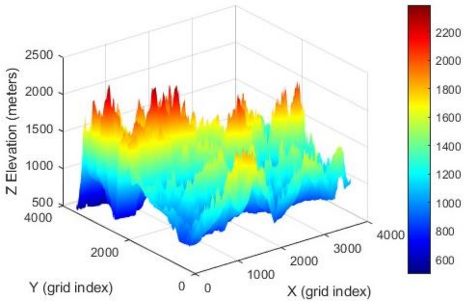

Fig.3. 3D topographic visualization of the Maden region illustrating elevation variability.

RELATED WORKS

Recent studies have demonstrated the growing importance of machine learning and data-driven approaches in wind speed forecasting and classification, particularly in regions characterized by complex topographies. Shen et al. proposed a full convolutional neural network model to reconstruct wind speed fields in mountainous areas, underlining the capacity of deep learning to capture spatial complexity in rugged terrains [4]. Similarly, Kim et al. improved ANN-based forecasting by integrating terrain-specific par ameters such as surface roughness, demonstrating the value of topographical adjustments in enhancing prediction accuracy over complex landscapes [5].

Advanced deep learning techniques, such as graph-based reconstruction [6] and support vector regression (SVR) models [7], have been successfully implemented to address nonlinearities in wind dynamics. Interpolation techniques adapted for mountainous regions have also been explored, where Reinhardt and Samimi compared various interpolation methods to improve data resolution in Central Asia's complex terrain [8].

Forecasting meteorological variables using ensemble and hybrid models is another area of significant progress. For instance, Sun et al. used machine learning to generate localized wind and temperature forecasts for the 2022 Beijing Winter Olympics [9], while Pauli et al. utilized satellite data to quantify fog and stratus formation in continental Europe [10]. The use of improved optimization algorithms such as Coati optimization in SVM models has also enhanced infrastructure safety under varying wind conditions [11]. Recent work by Mulewa et al. [12] introduced a Bagged-CNN architecture tailored for short-term wind power forecasting. Their approach demonstrated how combining ensemble learning with deep feature extraction improves generalization across diverse wind farms, supporting the growing trend toward hybrid CNN-based models.

Hybrid neural networks like LSTM and AR-LSTM have been applied in real-time forecasting for both meteorological [13] and agricultural applications [14], illustrating the versatility of recurrent models in spatiotemporal data analysis. Furthermore, environmental factors such as soil pH, runoff, and snowfall have been modeled using various machine learning frameworks, emphasizing their predictive capabilities in geophysical and climatic domains [15—17].

Similarly, Dai et al. [18] proposed a hybrid VMD–KELM model optimized with bio-inspired algorithms, achieving strong results in short-term wind prediction tasks by decomposing and reconstructing high-frequency components. A recent study by Natarajan and Singh [19] introduced a multi-objective optimized hybrid deep learning model using Slime Mould Optimization, demonstrating notable forecasting accuracy while maintaining model interpretability.

From a methodological perspective, multiple studies applied Bayesian optimization [20], ensemble decision trees [21], and empirical-statistical downscaling [22] to fine-tune hyperparameters and improve prediction robustness. These approaches align with our study, which employs K-Nearest Neighbor (KNN) modeling with Bayesian tuning for high-fidelity classification in the mountainous Maden region.

Ammar and Xydis [23] emphasized the critical role of preprocessing techniques, including outlier handling and decomposition, in improving the robustness of deep learning models for wind speed forecasting across different climate zones. Gürsoy et al. [24] utilized Geographic Information System (GIS) data combined with artificial neural networks for wind speed prediction in Karabük, Türkiye. Their use of regional meteorological and spatial features is thematically aligned with the terrain-informed modeling presented in this study.

In a recent study by Akinci et al. [25], a hybrid framework integrating Decision Tree (DT) algorithms with Large Language Models (LLMs) was proposed for wind power intensity classification. That work emphasized the importance of balancing interpretability and predictive accuracy by leveraging Shapley values and LLM-driven contextual insights. While their model achieved high accuracy for wind power density (WPD) classification in the Samandağ region, the computational complexity of LLM integration and the focus on textual-contextual explanations differentiate it from the present study. In contrast, our CNN–KNN model adopts a lightweight and scalable approach suitable for high-frequency temporal inputs and topographically challenging regions like Maden, with comparable classification performance but while maintaining comparable classification performance and offering reduced implementation complexity.

Despite the methodological advancements, most previous research has centered on offshore or flat terrain conditions [26-28], leaving a knowledge gap for inland mountainous regions.

Our study addresses this gap by applying explainable and structured classification tailored specifically to the Maden region's unique meteorological profile, guided by findings from recent works in similar challenging topographies [29 - 31].

In summary, while existing literature showcases a diverse application of AI models in wind speed estimation and meteorological forecasting, our study advances the state-of-the-art by proposing a hybrid CNN–KNN framework tailored to inland mountainous terrain. Unlike prior works that rely solely on either deep learning or traditional classifiers, our method integrates deep feature extraction using a 1D-CNN with interpretable classification via KNN. This approach achieves superior accuracy (98.75%) and offers a modular, explainable solution for wind speed level identification, particularly in data-limited and topographically complex regions—an approach rarely applied in previous studies [32 – 34]

METHODOLOGY

Dataset Description and Categorization

This study employs a meteorological dataset collected from the Maden region of Turkey, comprising 1096 daily observations. The dataset includes nine features (listed in Table 1), and the target variable is the daily average wind speed measured at 50 meters (DAWS50). To capture temporal patterns, a 30-day sliding window was applied, resulting in structured input matrices of shape 9×30 per sample. For each window, the wind speed of the last day was used to assign a class label according to the thresholds summarized in Table 2. This preprocessing step enabled the development of a temporal classification framework using a 1D-CNN for deep feature extraction and a traditional ML classifier for final decision-making. Figure 4 shows the distribution of the full raw dataset and class labels, while Figure 5 provides a zoomed-in view of the first 100 samples for clearer visualization of class boundaries.

TABLE I. Description and abbreviations of input and output features used in the classification model.

Data	Number	Abbreviations	
Inputs	1	Months	M
	2	Daily Average Pressure	DAP
	3	Daily Average Temperature (Celsius)	DATC
	4	Daily Average Temperature (Kelvin)	DATK
	5	Daily Average Soil Temperature (20 cm, Celsius)	DAST20C
	6	Daily 14 Local Relative Humidity (%)	D14LRH%
	7	Air Density (RO) [kg/m^3]	AD
	8	Wind Power Intensity (W/m^2)	WPI
Output	9	Daily Average Wind Speed (50)	DAWS50

TABLE II. Categorization of wind speed levels based on daily average wind speed at 50 meters.

Category	Daily Average Wind Speed (50 m) m/s	Numbering
Low	0-4.00	1
Medium	4.01-10.00	2
High	10.01-over	3

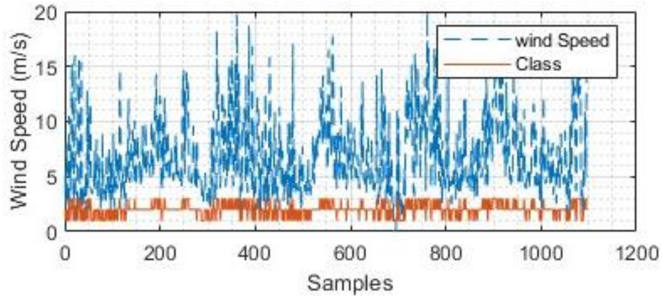

Fig.4. Raw Dataset Overview (N=1096)

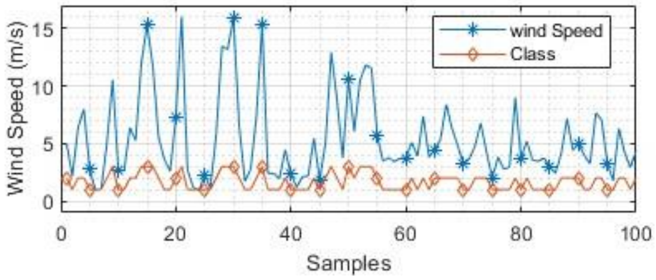

Fig.5. Zoomed View of First 100 Samples

Deep Feature Extraction Using 1D-CNN

A 1D convolutional neural network (CNN) was designed to learn deep temporal features from the input sequence. The network architecture consisted of three convolutional blocks with increasing filter sizes (32, 64, and 128), batch normalization, ReLU activations, max pooling layers, and a dropout layer. A global average pooling (GAP) layer was used to flatten the feature maps, providing a 128-dimensional deep feature vector for each input sequence. The network was trained for 25 epochs using the Adam optimizer, with an 85/15 training-validation split.

The output of the GAP layer—a 128-dimensional deep feature vector—was later used as input for machine learning classifiers, as described in the next section. The GAP operation compresses each feature map into a single scalar by averaging across the temporal dimension, as shown in Equation (1).

$$GAP_k = \frac{1}{T}\sum_{t=1}^{T} f_k(t) \tag{1}$$

where fk(t) is the activation of the k-th convolutional filter at time step t, and T is the total number of time steps in the feature map. As a result, a set of K feature maps yields a K-dimensional feature vector suitable for classification via traditional machine learning models.

CNN Architecture and Training

The CNN model was constructed using a sequential 1D architecture tailored for time-series meteorological inputs. The input consisted of nine features organized in a sliding window of 30 days. The architecture included the following components:

1. An input layer with a minimum sequence length of 30 and 9 features
2. Three convolutional layers with increasing filter sizes (32, 64, and 128) and kernel size of 3
3. Batch normalization and ReLU activation applied after each convolution layer
4. Max-pooling layers to reduce feature dimensionality and mitigate overfitting
5. A global average pooling (GAP) layer to compress the feature maps
6. A fully connected layer with three output units corresponding to the target wind speed levels
7. A softmax layer and classification layer for final decision-making

The complete architecture is illustrated in Figure 6.

Fig.6. Layer-wise architecture of the 1D CNN model for wind speed level classification.

The final classification layer uses the softmax activation function to produce class probabilities, as defined in Equation (2). The softmax function applied at the output layer transforms the network outputs z_i for each class i into normalized probabilities:

$$P(y = i \setminus \boldsymbol{z}) = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_j}}, \quad \text{for } i = 1, \ldots, C \qquad (2)$$

where C is the total number of classes. This allows the model to produce a probability distribution over wind speed levels. The softmax function converts the output vector $z \in R^C$ from the final fully connected layer into a probability distribution across the C output classes. It ensures that the predicted class probabilities sum to 1, enabling the model to make interpretable and probabilistic predictions.

The loss function applied during CNN training is expressed in Equation (3). During training, the CNN module was optimized using the categorical cross-entropy loss function, which measures the dissimilarity between the predicted softmax probabilities $P(y = i \backslash z)$ and the true label distribution y_i. Although final classification is performed by the KNN algorithm using the CNN-extracted deep features, this loss function was applied exclusively during the pre-training of the CNN to ensure that it learns discriminative representations from the input sequences.

$$\mathcal{L} = -\sum_{i=1}^{C} y_i \log\big(P(y = i \setminus \boldsymbol{z})\big) \qquad (3)$$

where C is the total number of classes, yi is the true class label in one-hot format, z denotes the output logits from the CNN, and $P(y = i \backslash z)$ is the softmax-predicted probability for class i. The loss $\boldsymbol{\mathcal{L}}$ is minimized during training to improve the feature extraction capability of the CNN module.

Proposed Hybrid CNN–ML Classification Framework

To further improve classification performance and demonstrate the integration of deep learning with traditional machine learning approaches, a hybrid framework was developed combining a one-dimensional Convolutional Neural Network (1D-CNN) for automatic feature extraction and a machine learning (ML) classifier for final decision-making. This approach was designed to capture both temporal-spatial patterns through convolutional layers and benefit from the generalization power of traditional ML algorithms.

The overall structure of the proposed hybrid classification system is presented in Figure 7. The flowchart illustrates each step of the pipeline, including input preparation, CNN-based feature extraction, and final classification using a KNN model. This modular approach enables effective integration of deep learning and traditional machine learning for wind speed level prediction in complex terrains.

Model performance was evaluated using standard metrics such as accuracy, confusion matrix, ROC-AUC, and precision-recall analysis.

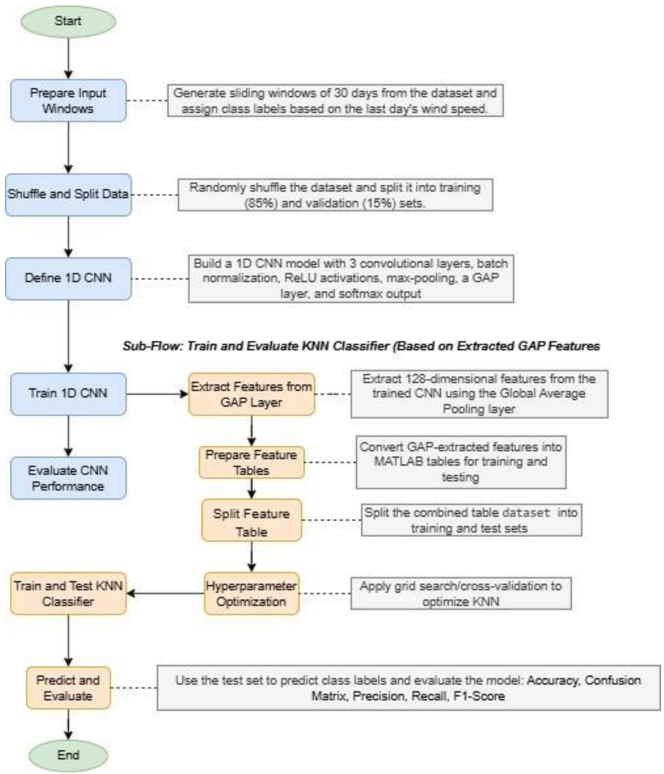

Fig. 7. Flowchart of the proposed hybrid CNN–KNN framework for wind speed level classification.

The KNN classification rule is based on majority voting among the kkk-nearest neighbors, as expressed in Equation (4). The K-Nearest Neighbor (KNN) classifier makes predictions based on the distance between the feature vector of a test sample x ∈ Rd and all feature vectors in the training set. For a given test sample, the predicted class $\hat{y}$ is determined by majority voting among the k closest training examples:

$$\hat{y} = arg \max_{c} \sum_{i \in N_k(x)} \delta(y_i = c) \tag{4}$$

where Nk(x) denotes the set of indices of the k-nearest neighbors of x, and δ(·) is the Kronecker delta function which returns 1 when the condition is satisfied.

Results and Discussion

The comparative analysis of three modeling strategies—standalone CNN, standalone machine learning (ML), and the proposed hybrid CNN+ML framework—demonstrates the clear advantages of integrating deep feature extraction with traditional classifiers for wind speed level identification in complex terrain.

Figure 6 presents the architecture of the 1D CNN model used for feature extraction. The network's sequential structure enabled it to capture temporal dependencies in the meteorological data over the 30-day window.

Training results of the standalone CNN model are illustrated in Figure 9, where both accuracy and loss curves over 50 epochs are shown. While the CNN successfully learned from the temporal sequences, the validation curve reveals fluctuations and possible overfitting. This supports the notion that CNN alone may have limited generalization capacity under complex terrain conditions like those in Maden.

The confusion matrix in Figure 8 reveals class-wise performance of the hybrid CNN–KNN model. The matrix shows that the model correctly identifies low, medium, and high wind speed levels with minimal misclassifications. This is further supported by the numerical values in Table 3, where the hybrid model achieves an accuracy of 98.75% with balanced precision, recall, and F1 scores—significantly outperforming both standalone CNN and KNN models.

To validate the discriminative power of the proposed approach, Figure 10 displays the ROC curves for each wind class. The near-perfect AUC values (>0.99) confirm high separability among the three classes. Similarly, Figure 11 illustrates class-specific precision-recall curves, with high PR-AUC values indicating strong robustness even under potential class imbalance.

Figures 12 and 13 provide comparative insights into model performance. Figure 12 contrasts test accuracies of various ML classifiers with the hybrid CNN–KNN framework, while Figure 13 shows training and test accuracy side by side. Both figures support the superiority and stability of the hybrid model, which performs consistently across different evaluation sets without sacrificing interpretability.

In summary, the hybrid CNN–KNN configuration addressed major limitations observed in individual models:

- The CNN model (91.25% accuracy) showed strong learning but lacked class-wise precision in low wind levels.
- Traditional ML classifiers (e.g., KNN at 84.14%) depended heavily on manual feature engineering and struggled with generalization.
- The proposed hybrid framework combined the automatic deep feature extraction of CNN with the simplicity and transparency of KNN, resulting in the most accurate, generalizable, and interpretable model.

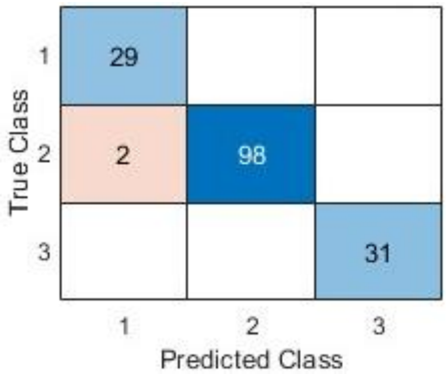

Fig. 8. Confusion matrix of the proposed hybrid CNN–KNN model on the test set

Figure 6 presents the performance of the standalone CNN model, illustrating the training and testing loss and accuracy over 50 epochs. While the model successfully learned from the input sequences, performance fluctuations and limited generalization suggest the potential for improvement through hybridization with traditional classifiers.

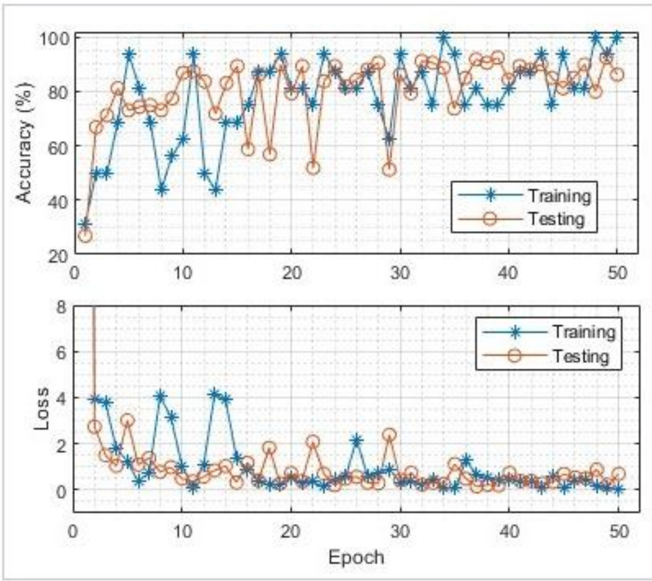

Fig. 9. Training and testing accuracy and loss curves of the standalone 1D CNN model over 50 epochs.

To further validate the model performance, ROC and PR curves were analyzed for all three classes. The hybrid CNN–KNN model achieved near-perfect ROC-AUC and PR-AUC scores across all three classes, as shown in Figures 10 and 11.

These results confirm the effectiveness of combining deep CNN features with traditional classifiers in handling class imbalances and improving class separability.

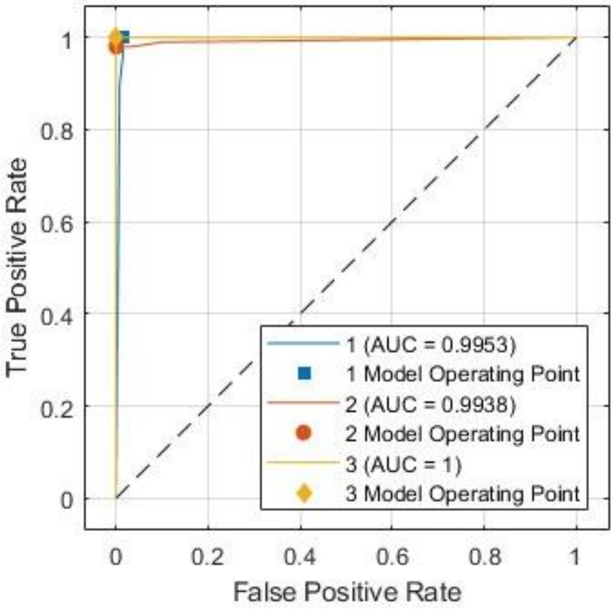

Fig. 10. ROC curves for each wind speed class, showing the true positive rate against the false positive rate and corresponding AUC values.

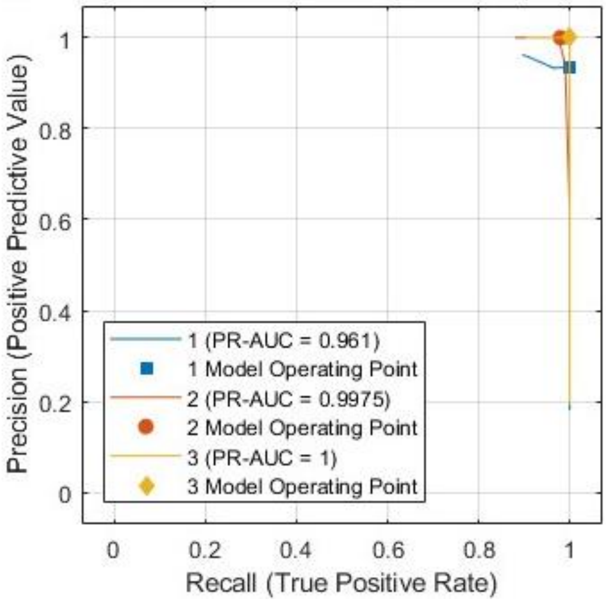

Fig. 11. Precision–Recall curves for each wind speed class, illustrating class-specific precision-recall tradeoffs and PR-AUC values.

In addition, Figures 12 and 13 present a comparative analysis across modeling strategies, confirming the superiority of the proposed hybrid framework. Table 3 presents a comparative summary of classification performance across three modeling strategies: standalone KNN, standalone CNN, and the proposed hybrid CNN–KNN model. While the CNN outperformed traditional KNN in validation accuracy and class-wise metrics, the hybrid architecture surpassed both with the highest test accuracy of 98.75%. The improvement demonstrates that using GAP-extracted deep features substantially enhances classifier performance, particularly in data-limited, terrain-complex environments like Maden.

TABLE III. Best performance metrics of CNN+KNN, CNN, and KNN models

Metric	CNN+KNN (%)	CNN (%)	KNN
Accuracy	98.750	91.25	84.14
Precision	98.750	92.5 (0.925)	84.14
Recall	98.750	92.5 (0.925)	84.14
F1 Score	98.750	92.5 (0.925)	84.14
Error Rate	1.250	8.75	15.85

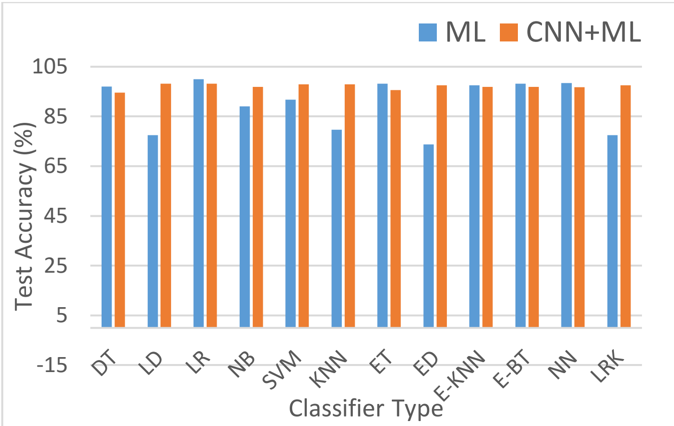

Fig. 12. Comparison of test accuracy between ML and CNN+ML classifier families.

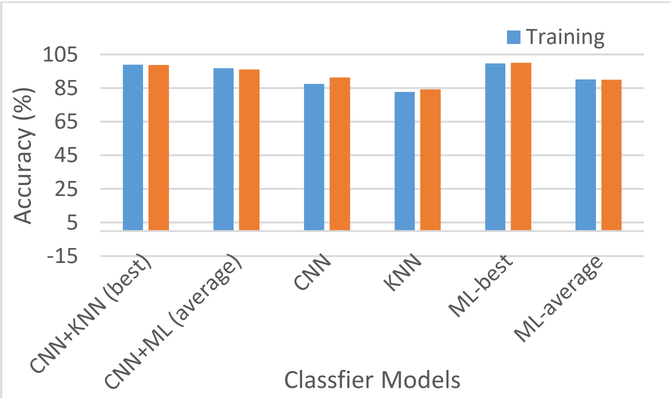

Fig. 13. Comparison of training and test accuracy for different classifier models.

Conclusion

A conclusion section is not required. Although a conclusion may review the main points of the paper, do not replicate the abstract as the conclusion. A conclusion might elaborate on the importance of the work or suggest applications and extensions.

This study introduced a high-fidelity classification framework for wind speed level identification in the mountainous Maden region of Turkey, where abrupt elevation and surface roughness variations present significant forecasting challenges. By leveraging a hybrid approach—combining deep feature extraction using a 1D-CNN with the lightweight, interpretable

K-Nearest Neighbor classifier—the proposed model achieved a test accuracy of 98.75%, outperforming both standalone CNN (91.25%) and KNN (84.14%) models.

The hybrid CNN–KNN model demonstrated strong generalization capability, particularly in complex terrain where wind behavior is influenced by topographic and microclimatic variability. The results were validated through confusion matrix analysis, accuracy metrics, and class-wise ROC and PR curves—all confirming the model's ability to effectively distinguish between low, medium, and high wind speed levels.

Unlike traditional ML models that rely on manual feature engineering, the proposed approach offers a scalable and automated solution for regional wind classification. Furthermore, the integration of terrain-sensitive input (as supported by Figures 1–3) ensures that the model is responsive to the spatial variability inherent to inland mountainous regions.

Overall, this work contributes a novel, transparent, and high-performance modeling solution for wind energy assessment in complex terrains. The proposed framework holds practical value for regional planning, turbine placement, and smart grid integration efforts in similar geographies.

Acknowledgment

This study was supported by the Bursa Uludağ University Scientific Research Projects (BAP) under Project ID: 2240.

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