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Particle Swarm Optimization based hybrid Deep Learning approach: Evidence from Europe for Predicting Air Quality Index

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***Abstract*—Air pollution remains a worldwide concern, and traditional machine-learning models often struggle to capture the complex, nonlinear relationships between the Air Quality Index (AQI) and its influencing variables. This study proposes two Particle Swarm Optimization (PSO)-based hybrid deep-learning approaches for predicting AQI using relevant environmental and meteorological variables. In the current study, one approach uses PSO, deep learning, and Linear Regression (LR) for feature selection, feature extraction, and AQI prediction, while the other employs PSO to optimize hyperparameters of deep learning. The study examines wind speed and direction using wind rose diagrams and evaluates the features' contributions using the Shapley Additive exPlanations (SHAP) analysis. Using the Wilcoxon signed-rank test, statistical validation shows that both approaches outperform existing methods at 34 monitoring locations. Specifically, the first approach is effective for 19 locations, with an average R^2 of 97.0%, while the second approach performs best for 33 locations, with an average R^2 of 98.17%. Our findings recommend implementing region-specific air quality policies across Europe. These findings can aid policymakers in designing targeted, effective, and data-driven interventions to improve public health and environmental resilience across Europe.**

***Index Terms*—Air pollution, AQI, PSO+FNN+LR, PSO+FNN, wind rose, SHAP**

I. INTRODUCTION

Air pollution remains one of the most critical environmental and public health challenges worldwide and is associated with severe respiratory and cardiovascular diseases. Despite past progress in air quality, a significant portion of the urban population is still exposed to air pollution that does not meet European standards and the guidelines set by the World Health Organization (WHO) [1]. In Europe, air pollution is linked to approximately 414,000 premature deaths annually and ambient air pollution in Europe causes a higher annual excess mortality rate than previously assumed, with 40% to 80% due to cardiovascular events [2], [3]. Despite policy efforts to improve air quality, many European cities still experience pollution levels exceeding the WHO, and air pollution remains the most significant environmental health risk [4] in Europe. Over 1,200 deaths in people under 18 years of age are attributed to air pollution [5]. Besides health issues, air pollution can significantly impact Europe's economy due to increased healthcare costs, reduced life expectancy, and lost working days across various sectors. It also damages greenery and ecosystems, degrades water and soil quality, and negatively impacts local ecosystems.

Traditional statistical models, such as multiple linear regression and ARIMA often struggle to capture the nonlinear and spatiotemporal complexities inherent in time series prediction and provide overfitting output [6], [7]. To address these limitations, researchers have increasingly turned to machine learning (ML) and Deep learning techniques, such as support vector regression, random forest, and artificial neural networks, which have demonstrated superior performance in handling complex air quality patterns [8]. However, hybrid approach combined with ML and deep learning techniques has the advantage over direct ML techniques to capture both linear and non-linear patterns of data, Noise Reduction, reducing overfitting, feature selection, ensemble learning, and time-series decomposition, to achieve more robust and accurate predictions [9], [10]. Hybrid machine and deep learning approach uses in many real-life applications specially in air pollution dynamics for predicting AQI [11]–[14].

This study proposes two hybrid PSO-based deep-learning frameworks for predicting AQI across 34 European cities for over the past 4 years (2021-2024) and achieved better outcome than traditional machine-learning and deep-learning. In first hybrid approach (PSO + FNN + LR), we integrated feature selection using particle swarm optimization (PSO), extracted features using Feedforward Neural Network (FNN) and predict AQI using linear regression (LR). In the second hybrid approach (PSO + FNN), we used PSO as hyper-parameter tuning for the Feedforward Neural Network (FNN) to achieve the optimum Neural Network model.

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The objectives of this study are as follows:

1) To develop a reliable hybrid model for predicting and forecasting AQI, supporting evidence-based air quality management and policy decisions.
2) Identifying the most influential environmental and meteorological variables, optimizing model configurations, and assessing the predictive accuracy of our hybrid approach using the performance evaluation metrics.
3) Use the Wilcoxon signed rank test to validate the statistical significance of the performance evaluation.
4) Use the SHapley Additive exPlanations (SHAP) analysis to identify the most significant features related to AQI value and capture the positive and negative changes of feature variables.
5) Use a wind rose diagram to analyze the deep relation of wind speed and wind direction to capture the flow of dust and particles in the atmosphere.

Section II discusses related studies and compare with our studies; section III discusses the dataset description and the correlation; section IV describes the used optimization and deep learning approaches that we used in our proposed approach; section V describes the experimental setup, and evaluation metrics; section VI describes the outcomes and discuss our findings to current research; while section VII offers the study's policy implication, limitation and conclusions.

II. RELATED WORK

Udristioiu, Mghouchi, and Yildizhan [11] proposed hybrid machine-learning models (IVS-DT, IFS and LS-NARMAX-DT) using Input Variable Selection, Decision Tree, Linear Regression and NARMAX for modeling, predicting and forecasting particulate matter (PM) concentrations in Craiova, Romania for 2 years with 1-minute frequency data with 15 meteorological and environmental parameters. The study also identified the most relevant variables, and the analysis showed that particulate matter had a strong linear relationship with AQI. Temperature, VOC, and O_3 were identified as the most influential predictors for PM concentrations and the proposed model achieved 95% and 93.4% R^2. But using this proposed approach, they only verified for a single area dataset.

Sarkar, Gupta, Keserwani, *et al.* [12] proposed a hybrid LSTM-GRU model using pre-processed data from Delhi, to predict the AQI value for PM2.5 from 2015 to 2021, which outperformed other standalone models with 36.11 MAE and 0.84 R^2 value where model's implementation requires huge computational power. It only includes four meteorological parameters and runs the model without additional hyper-parameter tuning.

Chen, Wang, and Zhang [13] tested a hybrid PSO-SVM model using a K-means clustering to conducting a case study in Beijing, China in 2017. The proposed model showed superior forecasting compared to three other models with the lowest MAPE = 0.1255. However, applying the K-means have oversimplified complex atmospheric patterns, and using K=4 clustering may not universally apply to other regions.

Sarkar, Keserwani, and Govil [15] proposed modified PSO (MPSO) based hybrid model to predict the AQI. The use of MPSO helps to increase the outcome of LSTM-BiRNN and LSTM-GRU in significant way. Using mean imputation for missing values and the Z-score method for outlier removal in the study may have introduced bias in the dataset. The study also did not use K-fold cross-validation which causes overfitting and provided a more robust evaluation of the models' performance. Liu and Guo [16] in Shanghai (2021-2022) reported that the LSTM-SSA model performed well and obtaining the lowest MAPE. Zhu, Zou, and Li [14] employed APSO-CNN-Bi-LSTM for multi-site AQI prediction which improved MAE by 9.375%, 6.667%, 2.276%, and 4.975%.

Ravindiran, Rajamanickam, Kanagarathinam, *et al.* [17] used four machine learning models with log transformation normalize and eliminated missing values and XGBoost performed the best. However, study did not incorporate hybrid techniques, which would have allowed for the investigation of more reliable predictive frameworks.

Maltare and Vahora [18] used different approaches without hybrid model to forecast the AQI for Ahmedabad (2015–2021) and found that SVM with an RBF kernel outperformed the other models. Mean imputation was employed for missing data, which may have introduced bias and oversimplified pollutant variability.

However, using our proposed approach in this study, we used 34 different cities of Europe continent with different types of feature variables and our approach can identify the non-linear relationship of feature and target variables. For this reason, our study achieves optimum outcome from the all the geo-location dataset. Our study also works 5-fold cross validation process which avoid the overfitting outcome from the dataset [19].

III. DATASET DESCRIPTION

In this study, we used daily time-series AQI datasets from 34 different locations in Europe for four years (2021-01-01 - 2024-12-31) and datasets are grouped into five different regions which are Eastern, Western, Central, Northern, and Southern Europe. We collected our datasets from the Open-Meteo open-source platform [20] which has free access for non-commercial uses. Our experimental dataset contains multiple variables where AQI is the target variable. The feature variables are grouped into three different categories- date (year, month and day), particulate and gaseous pollutants (PM2.5, PM10, CO, NO2, O3 and SO2) and rest of them are meteorological variables.

Table I presents the correlation for all features variables with the AQI across various parts of Europe where PM2.5 and PM10 are closely linked with higher AQI levels in all regions, especially in Eastern and Central Europe. Gases such as CO and NO2 also link with higher AQI in Eastern Europe. Ozone has a strong positive relation with AQI in the Northern part but a negative relation with others, except the Western part. Weather variables usually have a negative relationship with AQI as they help clear out pollutants. Overall, these differences suggest that improving AQI needs different strategies for each area.

Table I: Correlation between AQI and Feature Variables across Europe Region

	Europe Region				
Column	**Central**	**Eastern**	**Northern**	**Southern**	**Western**
year	0	0	0.08	0.02	0.03
month	-0.09	-0.05	-0.43	-0.24	-0.25
day	0	0.06	0.02	0.04	-0.02
PM2.5	0.89	0.97	0.43	0.86	0.84
PM10	0.88	0.94	0.48	0.82	0.81
CO	0.53	0.73	0.01	0.41	0.37
NO2	0.52	0.72	0	0.43	0.37
O3	-0.18	-0.49	0.72	-0.18	0.16
SO2	0.54	0.61	-0.09	0.42	0.47
Temperature (T)	-0.23	-0.45	-0.06	-0.17	-0.06
Relative humidity (RH)	0.07	0.4	-0.41	0.15	-0.22
Dew Point (DP)	-0.26	-0.41	-0.16	-0.18	-0.15
Snowfall (SF)	0.07	0.1	0.04	0.02	-0.06
Pressure (P)	0.23	0.27	0.15	0.37	0.34
Wind Speed (WS)	-0.27	-0.23	0.05	-0.29	-0.3
Wind Direction (WD)	-0.25	-0.08	0.11	-0.08	-0.31
Wind Gusts (WG)	-0.3	-0.34	0.1	-0.33	-0.29
Sunshine Duration (SD)	-0.08	-0.36	0.28	-0.07	0.17
Direct Radiation (DR)	-0.02	-0.35	0.32	-0.07	0.23

IV. BACKGROUND AND PROPOSED SCHEME

A. Background

In our study, we used several existing data per-processing, optimization and machine-learning techniques to construct the proposed hybrid approaches.

1) Pre-processing: StandardScaler is a pre-processing method which makes the features more uniform by eliminating the mean and scaling to unit variance [21], [22]. Equation 1 is the transformation equation for the StandardScaler:

$$z = \frac{x - \mu}{\sigma}. \tag{1}$$

where z is the standardized value, x is the input value, μ is the mean, and σ is the standard deviation.

2) Particle swarm optimization (PSO): PSO is a population-based optimization method that draws inspiration from the social behavior of fish and birds [23]. It is used in machine learning to enhance model efficiency and accuracy by optimizing feature selection and hyper-parameter tuning. PSO reduces dimensionality and overfitting in feature variable selection by determining the ideal subset of features that most influence model performance. By updating possible solutions in the parameter space, PSO strikes a balance between exploration and exploitation in hyper-parameter tuning. It has the capacity to avoid local minima which make it an effective tool for improving complicated models, frequently surpassing conventional grid or random search techniques.

3) Feedforward Neural Network (FNN): FNN is a deep learning algorithm which is characterized by unidirectional data flow, progressing from input to output without any feedback loops [24]. The network typically consists of an input layer, one or more hidden layers that utilize activation functions and an output layer that employs a linear activation function for forecasting real-valued objectives. During training, the neurons update its weights by minimizing a loss function and optimization methods like gradient descent.

4) Linear Regression (LR): Linear Regression (LR) is a basic supervised learning approach to predict a continuous target variable using one or more input characteristics [25].The linear regression equation is defined by 2.

$$\text{y } = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \epsilon. \tag{2}$$

where y is the dependent variable, $x_1, x_2, \ldots, x_n$ is the independent variables, β_0 is the intercept, $\beta_1, \beta_2, \ldots, \beta_n$ are coefficients, and ϵ is the error term.

B. Proposed Hybrid Approach

In our study, we proposed two hybrid approaches combined with PSO, FNN and LR that help to select features, tuning the hyperparameter and selecting features from the input variables of the AQI dataset. The two approaches are:

- **PSO + FNN + LR**: Helps for variables selection, feature extraction and AQI regression.
- **PSO + FNN**: Helps for hyper-parameter tuning and AQI regression.

The processes of PSO+FNN+LR and PSO+FNN are shown in Algorithm 1.

The description of these two hybrid approach are below:

1) Hybrid Model 1 (PSO + FNN + LR): In this approach, we used PSO for selecting important features variables from the dataset. By using the decision tree (DT) model with PSO technique in this approach, it updates the particles positions based on personal and global bests to avoid the local minima. Each particle modify the velocity using the own experience based on the neighbors and move towards the best solution in the search space. By this way, PSO provides the optimum subset of feature variables from the all set of features variables. Table II gives the details representation of optimum features using PSO for different cities of Europe where PM2.5, O_3 and Direct Radiation (DR) are the most important feature for all 34 cities. In this table, a checkmark indicates that the significant features was selected from all feature space using PSO for corresponding city, whereas a blank cell indicates that PSO did not selected the particular features for corresponding city. In the second part of this approach, we feed the optimum subset

```
Algorithm 1: Proposed Hybrid Approach
  Input: Dataset $D$ with features $X$ and target $Y$
  Output: Predicted AQI values
  Preprocessing:;
  1. Apply StandardScaler to normalize feature matrix
     $X \rightarrow X_{scaled}$;
  Model 1: PSO + FNN + LR (Feature Selection and
     Extraction);
  1. Initialize PSO parameters (population size, max
     iterations, velocity, etc.);
  2. Use PSO to search optimal subset of features from
     $X$;
  3. Select optimal feature subset $X_{PSO}$;
  4. Train a Feedforward Neural Network (FNN) using
     $X_{PSO}$;
  5. Extract hidden layer outputs $H_{FNN}$ from second
     hidden layer of FNN;
  6. Train a Linear Regression (LR) model using $H_{FNN}$
     as input to predict $Y$;
  7. Output predicted AQI values from LR;
  Model 2: PSO + FNN (Hyperparameter Tuning);
  1. Define search space for FNN hyper-parameters:
       Number of neurons in the first & second hidden
     layers $\in [10, 100]$
       Learning rate $\in [0.0001, 0.01]$
       Batch size $\in [16, 128]$;
  2. Initialize PSO with particles representing different
     combinations of hyper-parameters;
  3. For each particle, train FNN using corresponding
     hyper-parameters and evaluate fitness;
  4. Update particles using PSO update rules until
     convergence or max iterations;
  5. Select best hyperparameter set from PSO;
  6. Train final FNN model using selected
     hyper-parameters on training data;
  7. Output predicted AQI values from FNN;
```

of the features of PSO to the FNN model which contains two hidden layers using ReLU activation function where first layer contains 64 neurons and second layer contains 32 neurons. During training, FNN achieved the weight of minimum loss and provided a particular feature value from every neuron. Our approach captures the extracted feature values from the second layer which contains 32 neurons. This 32 features represents a robust, intermediate-level abstractions and non-linear representation of the input variables from the PSO which can identify the complex pattern of the input variable and balance raw and overly abstract features. These extracted features helps the machine-learning models to identify the complex pattern of the input variables [26], [27]. Our PSO + FNN + LR approach used these 32 extracted features from the second hidden layer and used as input feed for the Linear Regression (LR) to achieve the final prediction of the target variable. This hybrid approach combined the strengths of both deep learning (feature extraction) and traditional LR model to get robust prediction from the dataset.

Table II: Correlation between AQI and Feature Variables across Europe Region

City	Year	Month	Day	PM2.5	PM10	CO	NO2	O3	SO2	T	RH	DP	SF	P	WS	WD	WG	SD	DR
Amsterdam		✓		✓	✓		✓	✓			✓			✓	✓	✓		✓	
Athens				✓	✓		✓	✓						✓	✓		✓		✓
Barcelona		✓	✓	✓	✓		✓	✓	✓										
Berlin			✓	✓			✓	✓			✓	✓					✓		✓
Bruges				✓			✓	✓				✓		✓	✓				✓
Brussels				✓			✓	✓		✓		✓		✓			✓		✓
Budapest	✓	✓		✓		✓	✓	✓				✓		✓	✓		✓		✓
Cluj-Napoca		✓		✓				✓	✓		✓	✓	✓			✓	✓	✓	
Copenhagen	✓			✓			✓	✓						✓	✓		✓		✓
Frankfurt Airport	✓	✓		✓		✓	✓	✓			✓		✓	✓			✓		
Ghent	✓		✓	✓				✓			✓	✓				✓	✓	✓	
Graz Airport	✓		✓	✓	✓			✓	✓		✓			✓		✓		✓	✓
Helsinki		✓		✓			✓	✓					✓			✓		✓	✓
Isle Of Man		✓		✓				✓	✓	✓			✓	✓	✓		✓		✓
Istanbul Airport	✓			✓	✓	✓		✓			✓							✓	✓
Limerick		✓		✓	✓			✓	✓						✓		✓		
London			✓	✓		✓	✓	✓								✓		✓	✓
Lyon			✓	✓			✓	✓	✓			✓		✓				✓	✓
Madrid	✓	✓	✓	✓	✓		✓	✓				✓	✓	✓	✓				
Marseille			✓	✓	✓		✓	✓		✓					✓	✓		✓	✓
Milan	✓	✓	✓	✓				✓	✓		✓		✓						✓
Moscow				✓	✓		✓	✓						✓				✓	✓
Munich				✓	✓	✓	✓	✓								✓			✓
Nice		✓		✓				✓			✓		✓		✓			✓	✓
Nicosia		✓		✓	✓			✓			✓		✓		✓		✓		✓
Oslo		✓	✓	✓			✓	✓			✓		✓	✓	✓				✓
Paris		✓	✓	✓	✓		✓	✓				✓	✓					✓	✓
Poznań	✓		✓	✓			✓	✓	✓		✓		✓		✓	✓		✓	✓
Prague				✓		✓	✓	✓				✓	✓				✓	✓	
Reykjavík Airport	✓		✓	✓	✓	✓		✓					✓	✓		✓			
Rome		✓		✓		✓	✓	✓			✓		✓		✓	✓			✓
Stockholm		✓		✓			✓	✓			✓		✓		✓	✓			✓
Bern				✓				✓					✓	✓					
Findel Airport	✓			✓				✓		✓	✓		✓	✓	✓				✓

2) Hybrid Model 2 (PSO + FNN): PSO is used for parameter tuning and it is faster and gives optimum parameter than the grid or random search from the hyperparameter space. PSO is better from high dimensional space, it works well for continuous variables and learn from the history where grid or random search do not work [28]–[30]. In the second approach we used PSO as hyper parameter tuning for Feedforward Neural Network (FNN) model. In this approach, the first hidden layer neuron number, second hidden layer neuron number, learning rate and batch size of the FNN are tuning using PSO technique to achieve the optimum FNN model. The PSO takes the value range of the parameters as a search space and find the optimum solution for machine-learning model that minimizes the model's loss function.

PSO initialize a swarm of particles randomly with different combination of hyperparameter (first and second hidden layer number, learning rate and batch size) and their velocities. For each particle, the FNN is train and evaluate with the hyperparameter set, based on a performance evaluation. Each particle holds the best score (p_best) and follows own best and the global best (g_best) by founding the swarm. Finally, Repeat the evaluation and update steps for several iterations until it minimizes the error. Each particle updates its velocity and position using 3 and 4.

$$v_i^{t+1} = \omega v_i^t + c_1 r_1 (p_i^{\text{best}} - x_i^t) + c_2 r_2 (g^{\text{best}} - x_i^t) \quad (3)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (4)$$

Where, x_i^t: current position (hyperparameters) of particle i; v_i^t: velocity of particle i; p_i^{best}: best-known position (personal best) of particle i; g^{best}: global best position found by the swarm; ω: inertia weight controlling exploration; c_1, c_2: acceleration coefficients; r_1, r_2: random numbers in $[0, 1]$

In our experiment, we used the range of the first and second hidden layer neuron number 10 - 100; the learning rate range 0.0001 - 0.01; batch size range 16 - 128 for the FNN model and created the search space of the parameter combination from the defined range value and get the optimum parameter for 34 different cities which provide in table III.

Table III: Optimum FNN hyper-parameter using PSO.

City	First Layer Neuron	Second Layer Neuron	Learning Rate	Batch Size
Amsterdam	88	61	0.007	53
Athens	100	43	0.010	100
Barcelona	82	40	0.010	92
Berlin	60	42	0.010	101
Bern	73	39	0.009	90
Bruges	69	31	0.010	96
Brussels	60	36	0.010	95
Budapest	84	60	0.01	98
Cluj-Napoca	76	56	0.010	114
Copenhagen	73	32	0.010	82
Frankfurt Airport	91	60	0.010	107
Ghent	96	92	0.010	120
Graz Airport	85	50	0.010	92
Helsinki	73	36	0.010	83
Isle of Man	92	24	0.010	98
Istanbul Airport	75	54	0.008	116
Limerick	81	66	0.010	102
London	85	34	0.010	107
Findel Airport	69	31	0.010	82
Lyon	95	52	0.010	103
Madrid	82	41	0.006	95
Marseille	90	44	0.010	67
Milan	100	77	0.010	118
Moscow	85	60	0.010	96
Munich	88	41	0.010	99
Nice	64	45	0.010	90
Nicosia	89	37	0.010	99
Oslo	92	58	0.010	106
Paris	59	39	0.009	99
Poznań	66	44	0.010	97
Prague	87	30	0.007	103
Reykjavík Airport	48	52	0.008	93
Rome	69	28	0.010	84
Stockholm	97	39	0.010	83

V. EXPERIMENTAL SETUP AND PERFORMANCE EVALUATION

A. *Experimental setup*

We used several Python frameworks for implementation. Pandas [31] was used to pre-process and analyze the data. Scikit-learn [21] was used to build Decision Tree (DT), k-Nearest Neighbors (KNN), Linear Regression (LR) and evaluate their performance. TensorFlow [32] was applied to develop Feedforward Neural Network (FNN), Gated Recurrent Unit (GRU) and Long Short-Term Memory (LSTM). For model evaluation, we used the K-Fold Cross-Validation method [33] with K=5 to split the dataset into five parts.

B. *Performance Evaluation*

For performance evaluation, we use Root Mean Squared Error (RMSE), R^2 and Centered Root Mean Squared Error (CRMSE) [22], [34].

1) Root Mean Squared Error (RMSE): RMSE measures the prediction error‘s average magnitude, where a lower RMSE indicates better model performance. It is calculated by equation 5.

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (y_i - y_p)^2}{n}} \quad (5)$$

Where, y_i is the actual value, y_p is the predicted value and n is the number of observations.

2) R-squared (R^2): R^2 measures the fitness of the model for actual and predicted values, where a value closer to 1 indicates better predictive accuracy. It is calculated by equation 6.

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - y_p)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \quad (6)$$

Where, y_i is the actual value, y_p is the predicted value, $\bar{y}$ is the mean of actual values and n is the number of observations.

3) Centered Root Mean Squared Error (CRMSE): CRMSE measures the error after removing the mean bias between actual and predicted values, where a lower CRMSE indicates better agreement in pattern and variability. It is calculated by equation 7.

$$\text{CRMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left((y_i - \bar{y}) - (y_p - \bar{y_p}) \right)^2} \quad (7)$$

Where, y_i is the actual value, y_p is the predicted value, $\bar{y}$ is the mean of actual values, $\bar{y_p}$ is the mean of predicted values and n is the number of observations.

VI. RESULTS AND DISCUSSION

A. *Discussion on Performance*

Table V presents the R^2 values of different European cities using existing and hybrid approaches. The PSO + FNN gives the highest mean R2 for all region: Eastern Europe (99.33%), Western Europe (0.983), Central Europe (0.989), Northern Europe (0.978), and Southern Europe (0.972), which is better than other existing models. PSO+FNN+LR gave the second-highest result for Northern, Southern and Western regions. But for the Eastern region, DT resulted better than PSO+FNN+LR. For Amsterdam, PSO+FNN and PSO+FNN+LR give 2% and 1% better achievement than the DT and GRU, which indicates that our approach can work better than the machine-learning and Deep-Learning algorithms.

Table VI gives the overviews of RMSE where the PSO+FNN consistently provides optimum outcomes for most cities. PSO+FNN gives less RMSE than DT (0.3 less) and PSO+FNN+LR (0.4 less), achieving the lowest RMSE across most regions (e.g., 0.902 in Graz Airport) where PSO+FNN+LR performs slightly better than DT. PSO+FNN+LR gives better outcomes than PSO+FNN only for Munich, Athens, and Bern cities (1.037, 1.541, and 0.629). Out of 34 cities, PSO+FNN+LR gives better outcomes for 19 cities than DT. Northern Europe shows lower errors (average RMSE of 0.7946) using PSO + FNN, suggesting more predictable data patterns. Also traditional models like KNN and FNN show the poor RMSE in Milan (8.457) and in Madrid (9.654).

We also used Wilcoxon signed rank test [35], [36] from the performance evaluation metrics result for identifying the pair-wise statistical significance from the table V and VI results. Table IV shows the Wilcoxon rank test for both hybrid approaches and shows PSO+FNN gives significance outcome than all existing approaches and PSO+FNN+LR also gives better results for all existing methods except DT in out study.

Table IV: Statistical significance checking using the Wilcoxon test

Hybrid Approach	Metric	Existing Approach	Mean (Hybrid)	Mean (Existing)	Wilcoxon Stat	p-value	Decision
PSO+FNN	R^2	DT	0.982	0.968	5.5	1.2×10^{-7}	Significant
		GRU		0.937	0	3.6×10^{-12}	Significant
		KNN		0.797	0	3.6×10^{-12}	Significant
		LR		0.868	0	3.6×10^{-12}	Significant
		LSTM		0.850	0	3.6×10^{-12}	Significant
		FNN		0.808	0	3.6×10^{-12}	Significant
	RMSE	DT	1.12	1.45	6	5.1×10^{-11}	Significant
		GRU		1.940	0	3.6×10^{-12}	Significant
		KNN		4.210	0	3.6×10^{-12}	Significant
		LR		3.120	0	3.6×10^{-12}	Significant
		LSTM		3.060	0	3.6×10^{-12}	Significant
		FNN		3.060	0	3.6×10^{-12}	Significant
PSO+FNN+LR	R^2	DT	0.970	0.968	301	4.5×10^{-1}	Not significant
		GRU		0.937	55	2.1×10^{-7}	Significant
		KNN		0.797	0	3.6×10^{-12}	Significant
		LR		0.868	7	6.9×10^{-11}	Significant
		LSTM		0.850	0	3.6×10^{-12}	Significant
		FNN		0.808	0	3.6×10^{-12}	Significant
	RMSE	DT	1.51	1.45	384	9.4×10^{-1}	Not significant
		GRU		1.940	66	6.9×10^{-7}	Significant
		KNN		4.210	0	3.6×10^{-12}	Significant
		LR		3.120	4	2.5×10^{-11}	Significant
		LSTM		3.060	0	3.6×10^{-12}	Significant
		FNN		3.060	0	3.6×10^{-12}	Significant

Therefore, the proposed hybrid models, especially PSO+FNN, consistently perform better than used traditional methods and the accuracy supports of the real-time air quality monitoring and forecasting adoption, enabling policymakers to implement targeted interventions in high-pollution areas, such as traffic restrictions or industrial regulations.

Figure 1 shows the scatter of actual and predict values for Quarter 4, 2024 summarize test data where we can observe PSO + FNN gives the better result than others approach. In terms of CRMSE, the hybrid approach, PSO+FNN gives 0.242 better results than DT (0.299) and PSO+FNN+LR (0.538). Also, PSO+FNN gives 100% correlation with actual and predict output which means our approach gives better results for the AQI prediction.

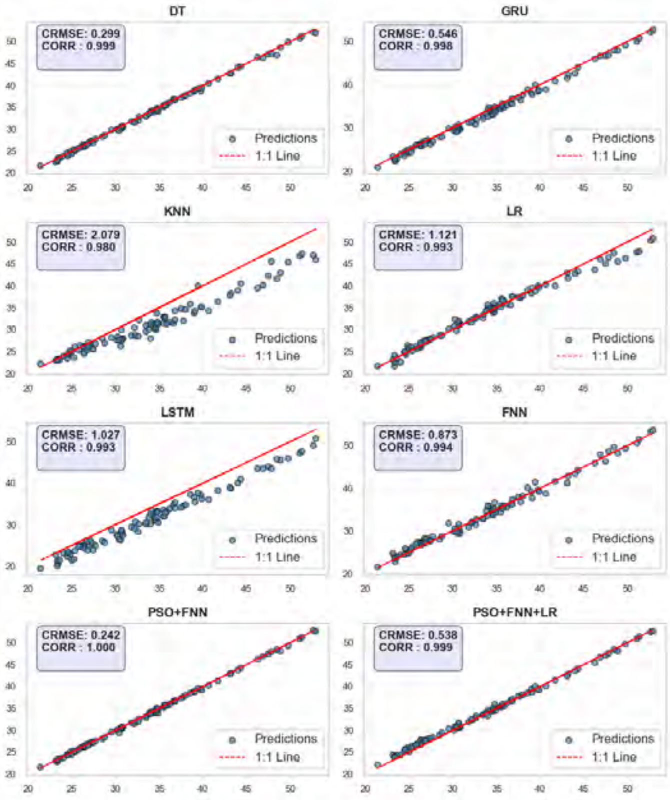

Fig. 1: Comparison of actual and predicted AQI for existing and proposed approaches.

Although PSO+FNN achieved better performance than the PSO+FNN+LR approach, the PSO+FNN+LR gives a better understanding of hybrid framework for feature selection, non-linear feature extraction and LR model prediction. It helps to identify the important features from the whole feature space using PSO methods and extract non-linear features from the important features which improve the predictive power of LR and FNN model. Therefore, PSO+FNN+LR provides a more transparent outcome compared with a fully neural-network-based and linear regression model. Also the results shows that in V and VI, the PSO+FNN+LR approach perform better than conventional machine-learning and deep-learning models in 19 out of 34 locations. Therefore, PSO+FNN+LR is retained as a useful comparative model for evaluating the contribution of nonlinear feature extraction combined with regression-based prediction.

B. *Wind Rose Diagram*

Figure 2 shows the wind rose diagram [37] across the five European regions. From this figure, Central, Eastern and Northern Europe have the dominant wind direction in South-West (SW) and South; Western Europe has dominant wind direction in South-West (SW) and West; Southern Europe has most wind direction from south direction. All has moderate wind speed which is mostly below 20 unit except the Southern Europe.

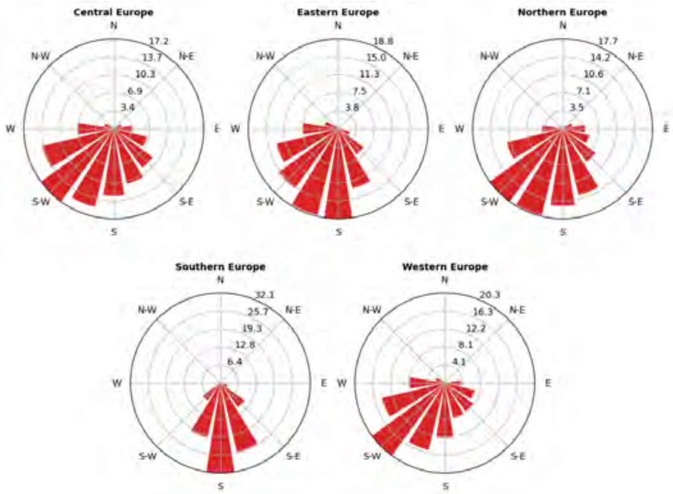

Fig. 2: Wind Rose Diagram of Wind Speed and Wind Direction.

Based on figure 2, the following observations can be made for the five regions:

1) Central: Southwesterly and southerly winds with moderate wind speeds may help disperse pollutants away from urban areas.
2) Eastern: Southern flow of winds, the warm air from the Balkans or Mediterranean increases the ozone levels and pollutants from industrial.
3) Northern: The wind direction of Northern Europe can cause relatively cleaner maritime air.
4) Southern: The wind flow carries Saharan dust and can increase PM10 and PM2.5 levels in the atmosphere of this region.
5) Western: Winds are influenced by Atlantic Ocean and creates a lower AQI and helps to dilute emissions from urban and industrial area.

C. *SHAP Analysis*

Figure **??** demonstrate the SHAP value, [38] a game theory-based explanation diagrams for the five European regions represent the comparative influence of the environmental and meteorological features on AQI predictions using a PSO + FNN hybrid model. Across all areas, PM2.5 and O3 (ozone) consistently show the most influential elements, indicating their dominant role in AQI variations. In Central and Eastern Europe, PM2.5's influence is more than 40, suggesting heavily polluted particulate levels significantly alter AQI outputs. In Northern Europe, O3 has slightly more impact than PM2.5 due to less industrial pollution but more vehicular emissions. Notably, wind gusts, dew point, and temperature show little influence, reflecting their contribution to pollutant dispersal and chemical reactions.

VII. Policy Implication, Limitation and Conclusion

A. *Policy Implication*

Our findings recommend the implementation of region-specific air quality policies across Europe. It will aid policymakers to design targeted, effective, and data-driven interventions in order to improve public health and environmental resilience across Europe.

Using wind-rose and SHAP analysis from figure 2 and **??** indicates that PM2.5 is one of the most influential variables in all region except northern region, which indicates to take necessary action to reduce particulate-matter through the control of industrial emissions, construction dust, and road-traffic-related particulate pollution. In Northern Europe, where O3 shows a stronger impact on AQI which indicates that policymakers should take necessary action to minimize the ozone precursor emissions, particularly NOx and volatile organic compounds from transport and urban sources. In Western Europe, industrial emission control, cleaner fuel transition, and traffic-emission regulation should be emphasized to show the strong relationship of ozone, and NO2 with AQI. In Southern region, wind patterns may carry the Saharan dust and increase particulate concentrations and policymakers should take action from this problem. In Western region, as Atlantic wind may impact dilute emissions, continue control of urban traffic emissions and industrial pollutants remain important policy initiatives to maintain lower AQI levels.

Also using the PSO+FNN model into national AQI forecasting systems can further support timely, evidence-based interventions and strengthen public health resilience. The robustness of PSO+FNN can be further applied to other regions to enhance the precision of AQI forecasting, and facilitate early warning systems such as traffic restrictions, industrial emission alerts, public health advisories, and dust-event warnings.

B. *Limitation and future work*

Our study utilized only the EU dataset and the characteristics of air pollution is much different in different continents, which results in a lack of generalizability. In the future, we will utilize data from various geographical locations. Another limitation is that to forecast the AQI, we need to forecast the feature variables or obtain the forecasted values from another source which will mitigate in future. Also, we will work in future to improve the proposed PSO + FNN + LR model.

C. *Conclusion*

In this research, we proposed two PSO based hybrid deep-learning approach to predict AQI of 34 different cities in Europe which give better outcome then existing machine-learning and deep-learning model. The proposed models outperform traditional techniques, achieving R^2 improvements of 2.9% and 1.5%, respectively, and RMSE reductions of 34% and 8.1% for PSO + FNN and PSO + FNN + LR, respectively. Our study also identifies the positive and negative relationships with feature and target variables using SHAP analysis which

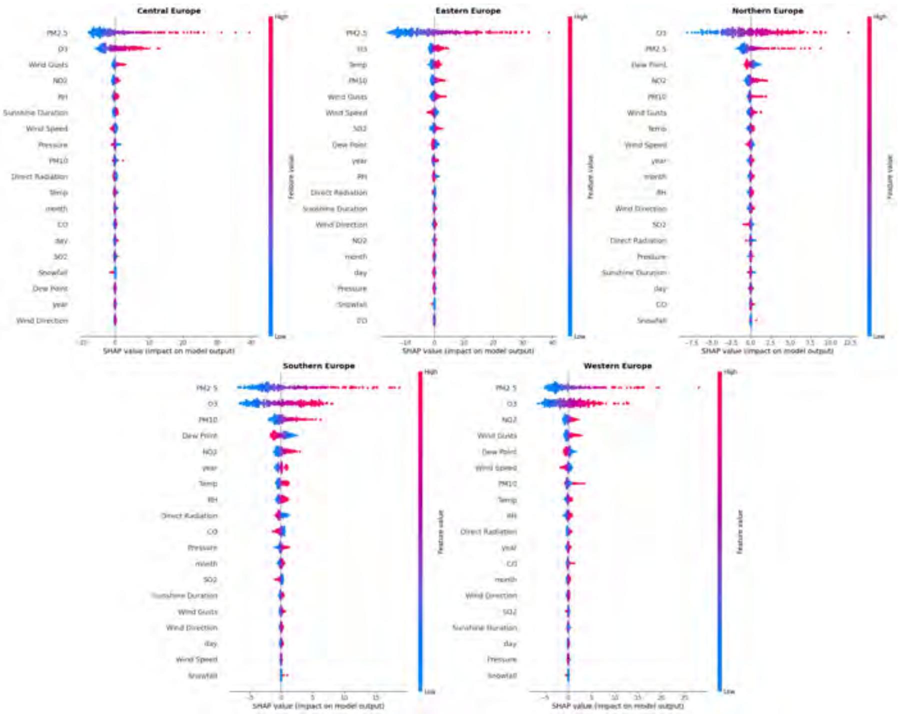

Fig. 3: SHAP analysis of the PSO + FNN model for five regions.

enlightens the deep understanding of our proposed model and feature variables to take effective policy analysis and decision making.

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DECLARATION OF AI TECHNOLOGY USAGE

We declare that no Artificial Intelligence (AI) technologies or AI-assisted tools were utilized in any capacity during the writing and preparation of this article.

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The authors declare that there is no conflict of interest regarding the publication of this paper.

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Muhammad Tanveer Islam: Conceptualization, Methodology, Software, Data curation, Writing Original draft preparation, Project administration. **Dr Ahsan Habib**: Methodology, Software, Writing, Reviewing, Supervision and Editing and Validation. **Dr Zobayer Ahmed**: Writing, Reviewing and Investigation. **Tasfia Tasneem Ahmed**: Writing- Reviewing, Investigation. **Hurmetun Nesa Labiba**: Writing- Reviewing and Editing.

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APPENDIX

A. R^2 Comparison

Table V: R^2 score for different cities using different models.

Region	City	DT	GRU	KNN	LR	LSTM	FNN	PSO+FNN	PSO+FNN+LR
Central	Graz Airport	0.989	0.976	0.838	0.906	0.933	0.948	**0.994**	0.964
	Prague	0.990	0.976	0.849	0.895	0.928	0.948	**0.991**	**0.991**
	Berlin	0.981	0.963	0.827	0.839	0.921	0.922	**0.989**	0.988
	Frankfurt Airport	0.957	0.969	0.822	0.856	0.928	0.917	**0.986**	0.960
	Munich	0.952	0.960	0.757	0.788	0.899	0.908	0.976	**0.980**
	Poznań	0.995	0.984	0.867	0.949	0.956	0.967	**0.996**	0.981
	Average	0.977	0.971	0.827	0.872	0.928	0.935	**0.989**	0.977
Eastern	Budapest	0.987	0.969	0.855	0.929	0.918	0.929	**0.992**	0.963
	Cluj-Napoca	**0.992**	0.972	0.853	0.931	0.919	0.941	0.990	0.979
	Moscow	0.995	0.987	0.852	0.996	0.954	0.953	**0.998**	0.995
	Average	0.991	0.976	0.853	0.952	0.930	0.941	**0.993**	0.979
Northern	Copenhagen	0.955	0.918	0.726	0.766	0.806	0.808	**0.980**	0.963
	Helsinki	0.913	0.939	0.686	0.840	0.816	0.854	**0.973**	0.969
	Reykjavík Airport	0.958	0.843	0.719	0.973	0.490	0.721	**0.976**	0.926
	Oslo	0.968	0.946	0.762	0.805	0.833	0.886	**0.984**	0.972
	Stockholm	0.914	0.934	0.679	0.844	0.829	0.853	**0.974**	0.949
	Average	0.942	0.916	0.714	0.846	0.755	0.824	**0.977**	0.956
Southern	Nicosia	0.974	0.935	0.817	0.794	0.727	0.849	**0.975**	0.971
	Athens	0.945	0.936	0.791	0.838	0.875	0.825	0.955	**0.972**
	Milan	0.993	0.987	0.843	0.966	0.965	0.965	**0.994**	0.976
	Rome	0.965	0.963	0.795	0.859	0.903	0.922	0.965	**0.967**
	Barcelona	0.977	0.936	0.826	0.911	0.866	0.835	**0.981**	0.979
	Madrid	0.917	0.650	0.788	0.831	0.571	-1.161	**0.953**	0.919
	Istanbul Airport	0.974	0.961	0.808	0.815	0.884	0.920	**0.983**	0.967
	Average	0.964	0.910	0.810	0.859	0.827	0.594	**0.972**	0.964
Western	Bruges	0.974	0.967	0.809	0.854	0.925	0.924	**0.988**	0.986
	Brussels	0.976	0.970	0.814	0.889	0.933	0.936	**0.988**	0.985
	Ghent	0.980	0.969	0.818	0.899	0.932	0.928	**0.989**	0.972
	Lyon	0.985	0.979	0.845	0.899	0.958	0.953	**0.989**	0.984
	Marseille	0.970	0.943	0.752	0.761	0.831	0.885	**0.984**	0.956
	Nice	0.966	0.688	0.743	0.836	0.608	0.132	**0.985**	0.971
	Paris	0.979	0.971	0.858	0.914	0.940	0.940	**0.990**	0.976
	Limerick	0.945	0.912	0.727	0.781	0.608	0.711	**0.979**	0.964
	Findel Airport	0.983	0.959	0.796	0.841	0.881	0.865	**0.987**	0.964
	Amsterdam	0.963	0.963	0.801	0.873	0.910	0.912	**0.981**	0.976
	Bern	0.984	0.947	0.780	0.824	0.872	0.879	0.988	**0.993**
	Isle of Man	0.925	0.884	0.723	0.876	0.623	0.715	**0.943**	0.933
	London	0.973	0.971	0.848	0.897	0.936	0.918	**0.984**	0.982
	Average	0.970	0.933	0.793	0.857	0.843	0.823	**0.983**	0.973

B. RMSE Comparison

Table VI: RMSE score for different cities using different models.

Region	City	DT	GRU	KNN	LR	LSTM	FNN	PSO+FNN	PSO+FNN+LR
Central	Graz Airport	1.147	1.821	4.771	3.585	3.041	2.681	**0.902**	2.086
	Prague	1.192	1.824	4.642	3.765	3.096	2.663	**1.105**	1.118
	Berlin	1.254	1.75	3.841	3.646	2.53	2.534	**0.971**	1.018
	Frankfurt Airport	1.752	1.528	3.61	3.231	2.303	2.501	**1.023**	1.735
	Munich	1.617	1.566	3.86	3.461	2.486	2.38	1.17	**1.037**
	Poznań	1.177	2.056	6.051	3.441	3.394	2.941	**1.032**	2.193
	Average	1.357	1.758	4.463	3.522	2.808	2.617	**1.033**	1.531
Eastern	Budapest	1.653	2.466	5.606	3.862	3.994	3.717	**1.28**	2.696
	Cluj-Napoca	**1.129**	2.236	5.13	3.361	3.754	3.25	1.255	1.903
	Moscow	1.225	2.138	7.104	1.052	3.919	3.937	**0.802**	1.236
	Average	1.336	2.280	5.947	2.758	3.889	3.6347	**1.112**	1.945
Northern	Copenhagen	1.277	1.606	3.159	2.86	2.434	2.477	**0.818**	1.088
	Helsinki	1.574	1.302	2.931	2.125	2.188	2	**0.857**	0.917
	Reykjavík Airport	0.958	1.846	2.452	0.673	3.312	2.499	**0.599**	1.309
	Oslo	1.143	1.48	3.213	2.929	2.362	2.124	**0.85**	1.125
	Stockholm	1.518	1.382	3.04	2.095	2.173	2.035	**0.849**	1.203
	Average	1.294	1.523	2.959	2.136	2.494	2.227	**0.794**	1.128
Southern	Nicosia	1.385	2.231	3.739	3.988	4.419	3.389	**1.371**	1.489
	Athens	2.175	2.339	4.321	3.774	3.259	3.808	1.984	**1.541**
	Milan	1.719	2.382	8.457	3.891	4.003	3.934	**1.624**	3.057
	Rome	1.807	1.9	4.422	3.612	3.121	2.775	**1.773**	1.804
	Barcelona	1.652	2.682	4.444	3.192	3.807	4.079	**1.453**	1.519
	Madrid	2.556	4.633	4.357	3.863	5.542	9.654	**2.026**	2.601
	Istanbul Airport	1.484	1.818	4.053	3.973	3.093	2.586	**1.218**	1.665
	Average	1.825	2.5693	4.828	3.756	3.892	4.318	**1.636**	1.954
Western	Bruges	1.484	1.674	4.16	3.606	2.577	2.605	**0.996**	1.11
	Brussels	1.541	1.706	4.42	3.383	2.547	2.543	**1.11**	1.186
	Ghent	1.476	1.834	4.568	3.376	2.674	2.807	**1.098**	1.715
	Lyon	1.484	1.751	4.826	3.865	2.49	2.655	**1.264**	1.51
	Marseille	1.296	1.719	3.631	3.568	2.763	2.438	**0.951**	1.5
	Nice	1.289	2.92	3.61	2.888	3.969	4.78	**0.878**	1.209
	Paris	1.577	1.828	4.07	3.177	2.593	2.613	**1.089**	1.681
	Limerick	1.269	1.519	2.849	2.459	2.959	2.585	**0.783**	1.025
	Findel airport	0.992	1.515	3.417	3.019	2.571	2.691	**0.845**	1.409
	Amsterdam	1.647	1.629	3.76	3.036	2.546	2.532	**1.172**	1.323
	Bern	0.943	1.634	3.502	3.11	2.565	2.411	0.819	**0.629**
	Isle of Man	1.333	1.657	2.601	1.713	2.991	2.599	**1.094**	1.261
	London	1.463	1.519	3.465	2.837	2.223	2.505	**1.126**	1.18
	Average	1.369	1.762	3.759	3.079	2.728	2.751	**1.017**	1.288