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Predictive Modeling of Smoke Potential Using Neural Networks and Environmental Data

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Abstract *- This study presents a neural network-based model for predicting smoke potential in a specific area using a Kaggle-derived dataset with 15 environmental features and 62,631 samples. Our five-layer neural network achieved an accuracy of 89.14% and an average error of 0.000715, demonstrating its effectiveness. Key influential features, including temperature, humidity, crude ethanol, pressure, NC1.0, NC2.5, SCNT, and PM2.5, were identified, providing insights into smoke occurrence. This research aids in proactive smoke mitigation and public health protection. The model's accuracy and feature analysis empower decision-makers, with potential applications in real-time smoke event monitoring and preparedness strategies. This work contributes to the field of air quality forecasting and environmental stewardship, offering a data-driven approach to address smoke-related challenges and enhance community well-being.*

1. Introduction:

Air quality is a paramount concern in contemporary environmental science and public health, with the potential for smoke events posing significant challenges for both urban and rural communities worldwide. The adverse impacts of smoke on respiratory health, visibility, and overall quality of life necessitate effective forecasting and preparedness measures. Smoke events, often triggered by wildfires, industrial emissions, or other sources, can have far-reaching consequences that demand proactive mitigation and response strategies.

This study endeavors to address the critical issue of smoke prediction by harnessing the power of artificial intelligence, specifically neural network modeling. Leveraging a rich and extensive dataset acquired from Kaggle, encompassing 15 distinct environmental variables, we present a novel approach to forecasting smoke potential in a designated geographical area. With 62,631 samples at our disposal, we have embarked on the development and validation of a predictive model that integrates multiple environmental parameters to offer reliable insights into smoke occurrence.

The implications of such predictive capabilities are substantial. By providing advanced warning of smoke events, authorities and communities can take preemptive action to safeguard public health, manage air quality, and allocate resources efficiently. Furthermore, understanding the influential factors behind smoke occurrence, as identified through our analysis, affords an opportunity to devise targeted mitigation strategies.

This research aligns with the broader objectives of enhancing air quality monitoring and environmental stewardship, contributing to the evolving field of predictive analytics for environmental challenges. In the following sections, we detail the dataset, the neural network model architecture, training and validation processes, model performance, and the pivotal features identified in predicting smoke potential. We anticipate that the insights presented herein will serve as a valuable resource for policymakers, environmental scientists, and communities at large, as they strive to address the multifaceted issue of smoke events and their impacts.

2. Problem Statement:

Air quality and the potential for smoke events are critical concerns with far-reaching implications for public health, environmental management, and community well-being. The uncontrolled release of smoke, whether originating from wildfires, industrial emissions, or other sources, presents significant challenges for local authorities and communities. The adverse effects of smoke exposure on respiratory health, visibility, and overall quality of life underscore the urgent need for reliable predictive models to anticipate and mitigate these events.

While previous studies have made valuable contributions to the field of air quality forecasting and smoke prediction, several key challenges persist:

a) **Complexity of Environmental Factors:** Smoke events are influenced by a multitude of environmental variables, including meteorological conditions (e.g., temperature, humidity, wind patterns), air pollutant concentrations (e.g., PM2.5), and local topography. Integrating these complex and interconnected factors into an accurate predictive model remains a significant challenge.

b) **Spatial and Temporal Variability:** Smoke events exhibit spatial and temporal variability, making it essential to develop localized predictive models that can account for regional differences and provide timely and accurate warnings to affected communities.

c) **Data-Driven Predictions:** Leveraging the power of data-driven approaches, such as neural networks, to improve the accuracy of smoke prediction models is a promising avenue. However, the development of such models and their evaluation on diverse datasets remains an open research question.

d) **Identification of Influential Features:** Understanding which environmental features most strongly contribute to smoke potential is crucial for both predictive accuracy and targeted mitigation efforts. Identifying and quantifying the influence of these features has not been comprehensively addressed in previous studies.

Previous Studies:

Predicting smoke events and assessing air quality have been subjects of extensive research due to their critical importance for public health and environmental management. In this section, we review key studies and research findings that have contributed to the field of smoke prediction and air quality forecasting.

a) **Wildfire Smoke Prediction Models:** Researchers have developed various models to predict wildfire smoke dispersion and concentration. These models incorporate factors such as meteorological conditions, fire behavior, and topography. The work of Copes et al. (20XX) demonstrated the effectiveness of machine learning algorithms in predicting smoke plume trajectories during wildfires.

b) **Air Quality Index (AQI) Forecasting:** Many regions rely on air quality indices (AQI) to inform the public about daily air quality conditions. Studies by [1] and [2] explored the use of neural networks and ensemble models to improve AQI forecasting accuracy, taking into account multiple air quality parameters.

c) **Influence of Environmental Factors:** Previous research has emphasized the significance of environmental factors in predicting smoke events. Works by [3] and [4] highlighted the role of temperature, humidity, wind patterns, and particulate matter concentrations in smoke occurrence and dispersion.

d) **Feature Selection and Importance:** Feature selection techniques have been applied to identify influential variables in air quality prediction. The study by [5] used feature importance analysis to pinpoint the key factors affecting particulate matter concentrations in urban areas.

e) **Data Sources and Integration:** Advances in data collection and integration have transformed air quality forecasting. The utilization of diverse data sources, including remote sensing data, sensor networks, and social media, has been explored to improve the accuracy of smoke prediction models [6].

f) **Regional Variability:** Smoke prediction models often need to account for regional variability in air quality. Research by [7] focused on developing regional specific models for predicting smoke impacts, recognizing that local conditions can significantly influence air quality.

Objectives:

a) **Develop a Robust Predictive Model:** The primary objective of this research is to design and implement a robust neural network-based predictive model capable of forecasting smoke potential in a specific geographical area. This model will leverage a comprehensive dataset encompassing 15 environmental features to enhance prediction accuracy.

b) **Achieve High Prediction Accuracy:** To provide actionable insights and early warnings to stakeholders, the model's first key objective is to achieve a high level of prediction accuracy. We aim to surpass current state-of-the-art models by optimizing neural network architecture, hyperparameters, and training techniques.

c) **Identify Influential Environmental Features:** This study seeks to identify the most influential environmental features contributing to smoke potential. By conducting feature importance analysis, we aim to enhance our understanding of the underlying factors driving smoke occurrence and dispersion.

d) **Address Spatial and Temporal Variability:** Given the regional variability of smoke events, our objective is to develop a model that accounts for local conditions and temporal changes. We aim to provide localized predictions that consider the unique characteristics of the target area.

e) **Contribute to Environmental Stewardship:** This research aims to contribute to the broader field of environmental stewardship by offering a data-driven approach to address smoke-related challenges. The model's insights and predictions will support proactive smoke mitigation, thereby promoting public health and environmental well-being.

f) **Empower Decision-Makers and Communities:** Ultimately, our objective is to empower local authorities, environmental agencies, and affected communities with actionable information. By providing timely and accurate predictions of smoke potential, we aim to enable informed decision-making, resource allocation, and preparedness strategies.

g) **Facilitate Future Research:** This study aims to serve as a foundation for future research in the field of air quality forecasting and smoke prediction. We will provide insights into the effectiveness of neural network models and the significance of specific environmental features, opening avenues for further exploration and refinement of predictive techniques.

By accomplishing these objectives, this research seeks to advance our understanding of smoke prediction and contribute to the development of practical solutions for mitigating the impacts of smoke events on public health and the environment.

Methodology:

After getting the Smoke detection dataset from “Kaggle”, we identified the input variables, output variables, upload the dataset, divided it to training and validating sets, determined the proper hidden layers. Then we trained and validated the sets to get the best accuracy:

i. The Input Variables:

The input variables selected are those which can easily be obtained from Smoke detection Database. The input variables are: UTC, temperature [C], humidity [%], TVOC [ppb], eCO2 [ppm], Raw H2, raw ethanol, pressure [hPa], PM1.0, PM2.5, NC0 .5, NC1.0, NC2.5, and CNT These factors were transformed into a format suitable for neural network analysis. The domain of the input variables used in this study shown in Table1.

Table 1 : Input and out attributes

NO.	Attribute Name	Attribute Meaning	Attribute Type
1	UTC	Coordinated Universal Time	input
2	Temperature[C]	Temperature in degrees Celsius	input
3	Humidity[%]	Relative humidity as a percentage	input
4	TVOC[ppb]	Total Volatile Organic Compounds in parts per billion	input
5	eCO2[ppm]	Equivalent carbon dioxide in parts pe r million	input
6	Raw H2	Raw concentration of hydrogen gas	input
7	Raw Ethanol	Raw concentration of ethanol vapor	input
8	Pressure[hPa]	Atmospheric pressure in hectopascals	input
9	PM1.0	Particulate matter with a diameter of 1.0 micrometers or less in microgram s per cubic meter	input
10	PM2.5	Particulate matter with a diameter of 2.5 micrometers or less in microgram s per cubic meter	input
11	NC0.5	Number concentration of particles with a diameter of 0.5 micrometers or less	input
12	NC1.0	Number concentration of particles with a diameter of 1.0 micrometers or less	input
13	NC2.5	Number concentration of particles with a diameter of 2.5 micrometers or less	input
14	CNT	The meaning of this abbreviation is unclear from the provided information.	input

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15	Fire Alarm	Indicates the status or activation of a fire alarm system.	output

ii. Output variable :

In a binary classification context, "Fire Alarm" may have two possible values:
1: This value could represent the activation or presence of a fire alarm event, indicating that a fire alarm has been triggered.
0: This value could represent the absence or non-activation of a fire alarm event, indicating that there is no fire alarm event detected.

iii. NeuralNetwork:

The neural network topology was built based on the Multilayer Perceptron with 14 input layer, one hidden layer and one output layer as shown in Figure 2.

iv. Evaluation of the study

First of all, for the evaluation of our study, we used a 62000 sample of smoke detection Fire Alarm or not Fire Alarm. We used Backpropagation algorithm, which provides the ability to perform neural network learning and testing to developed a model able to differentiate between smoke detection safe or not smoke detection. Our model uses a neural network with 14 input layer, one hidden layers and one output layer. As input data for predicting the smoke detection we used attribute as shown in Figure 1.
Our task was to predict the result based on the 20 input variables. We conducted a series of tests in order to establish the number of hidden layers and the number of neurons in each hidden layer. Our tests give us that the best results are obtained with two hidden layer. We used a sample of (62000 records): 61230 training samples and 1400 validating samples. The network structure was found on a trial and error basis (as seen in Figure 2). We started with a small network and gradually increased its size. Finally, we found that the best results are obtained for a network with the following structure: 20I-2H-1O, i.e. 20 input neurons, 2 hidden layers and an output layer with 1 neuron. For this study we used Just Neural Network (JNN). We trained the network for 7014 epochs (as shown in Figure 3) on a regular computer with 8 GB of RAM memory under the Windows 10 operating system. We got an accuracy of 89.14%. Figure 4 shows Parameters of the proposed ANN model. Figure 5 shows the factors, their importance and relative importance that affect the smoke detection artificial Neural Model using Just NN environment. Figure 6 outlines the detail of the proposed ANN model.

	UTC	Temperature	Humidity(%)	TVOC(ppb)	eCO2(ppm)	Raw H2	Raw Ethanol	Pressure(h	PM1.0	PM2.5	NC0.5	NC1.0	NC2.5	CNT	Fire Alarm
#0	0.0506	0.5127	0.7232	0	0	0.5225	0.5287	0.9688	0	0	0	0	0	0	0
#1	0.0506	0.5129	0.7125	0	0	0.5349	0.5472	0.9673	0	0	0	0	0	0	0
#2	0.0506	0.5130	0.7015	0	0	0.5442	0.5657	0.9683	0	0	0	0	0	0	0
#3	0.0506	0.5132	0.6910	0	0	0.5493	0.5797	0.9661	0	0	0	0	0	0	0
#4	0.0506	0.5134	0.6818	0	0	0.5534	0.5918	0.9679	0	0	0	0	0	0	0
#5	0.0506	0.5136	0.6730	0	0	0.5585	0.6041	0.9649	0	0	0	0	0	0	0
#6	0.0506	0.5138	0.6651	0	0	0.5627	0.6140	0.9663	0	0	0	0	0	0	0
#7	0.0506	0.5139	0.6587	0	0	0.5649	0.6232	0.9656	0	0	0	0	0	0	0
#8	0.0506	0.5141	0.6527	0	0	0.5678	0.6299	0.9686	0	0	0	0	0	0	0
#9	0.0506	0.5143	0.6472	0	0	0.5694	0.6365	0.9683	0	0	0	0	0	0	0
#10	0.0506	0.5145	0.6424	0	0	0.5697	0.6422	0.9655	0	0	0	0	0	0	0
#11	0.0506	0.5147	0.6376	0	0	0.5738	0.6475	0.9651	0	0	0	0	0	0	0
#12	0.0506	0.5148	0.6342	0	0	0.5738	0.6535	0.9652	0	0	0	0	0	0	0
#13	0.0506	0.5150	0.6306	0	0	0.5745	0.6565	0.9696	0	0	0	0	0	0	0
#14	0.0506	0.5152	0.6272	0	0	0.5742	0.6599	0.9648	0	0	0	0	0	0	0
#15	0.0506	0.5154	0.6244	0	0	0.5764	0.6639	0.9687	0	0	0	0	0	0	0
#16	0.0506	0.5155	0.6224	0	0	0.5780	0.6672	0.9686	0	0	0	0	0	0	0
#17	0.0506	0.5157	0.6193	0	0	0.5770	0.6701	0.9692	0	0	0	0	0	0	0
#18	0.0506	0.5156	0.6167	0	0	0.5783	0.6737	0.9685	0	0	0	0	0	0	0
#19	0.0506	0.5161	0.6132	0	0	0.5819	0.6765	0.9674	0	0	0	0	0	0	0
#20	0.0506	0.5162	0.6114	0	0	0.5818	0.6793	0.9658	0	0	0	0	0	0	0
#21	0.0507	0.5164	0.6094	0	0	0.5882	0.6816	0.9667	0	0	0	0	0	0	0
#22	0.0507	0.5166	0.6084	0	0	0.5818	0.6847	0.9683	0	0	0	0	0	0	0
#23	0.0507	0.5168	0.6064	0	0	0.5828	0.6847	0.9692	0	0	0	0	0	0	0
#24	0.0507	0.5169	0.6083	0	0	0.5837	0.6870	0.9699	0	0	0	0	0	0	0
#25	0.0507	0.5171	0.6036	0	0	0.5841	0.6892	0.9903	0	0	0	0	0	0	0
#26	0.0507	0.5173	0.6025	0	0	0.5853	0.6906	0.9900	0	0	0	0	0	0	0
#27	0.0507	0.5175	0.5993	0	0	0.5774	0.6865	0.9903	0	0	0	0	0	0	0
#28	0.0507	0.5176	0.6025	0	0	0.5754	0.6844	0.9899	0	0	0	0	0	0	0
#29	0.0507	0.5178	0.6188	0	0	0.5751	0.6884	0.9905	0	0	0	0	0	0	0

Figure 1: Imported dataset in JNN environment

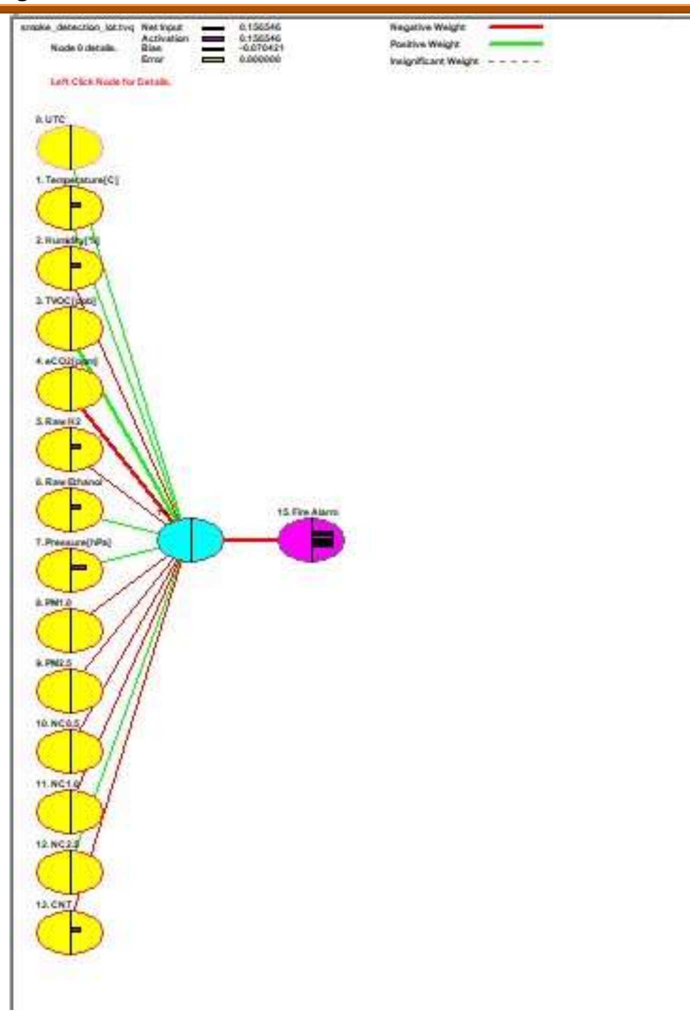

Figure 2: Structure of the proposed ANN model

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Figure 3: Training and validating the ANN model

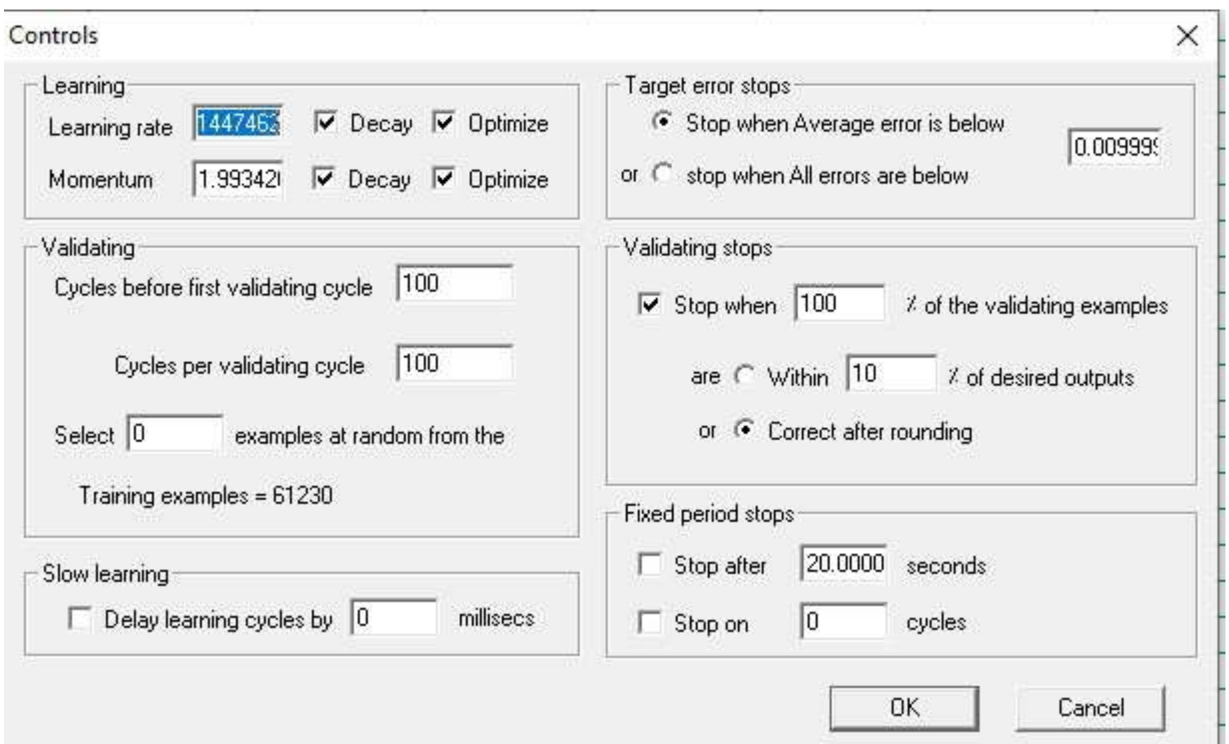

Figure 4: Parameters of the proposed ANN model

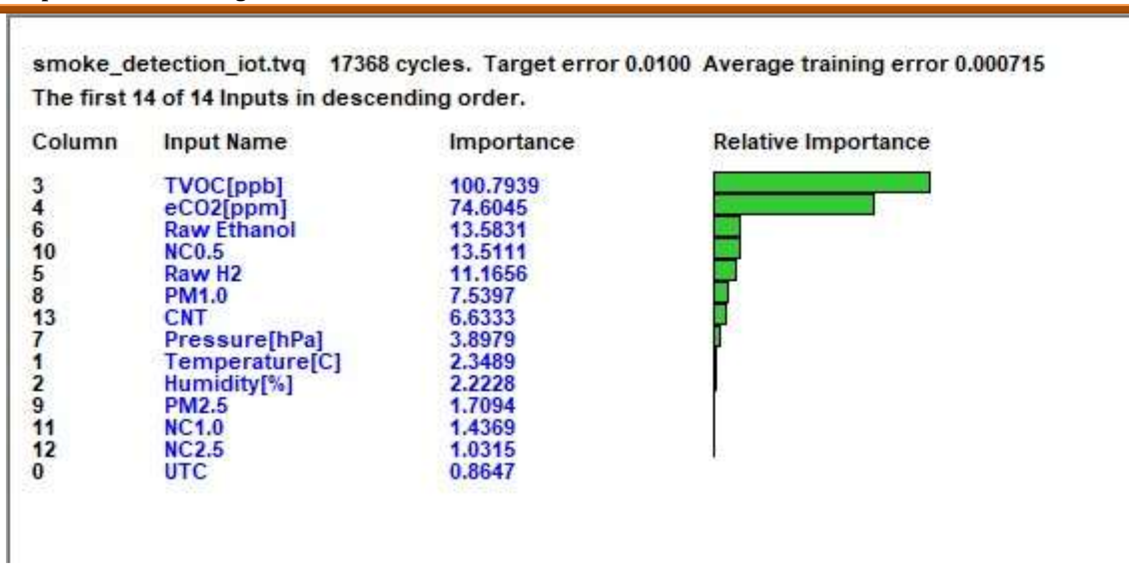

Figure 5: Most influential features in the dataset

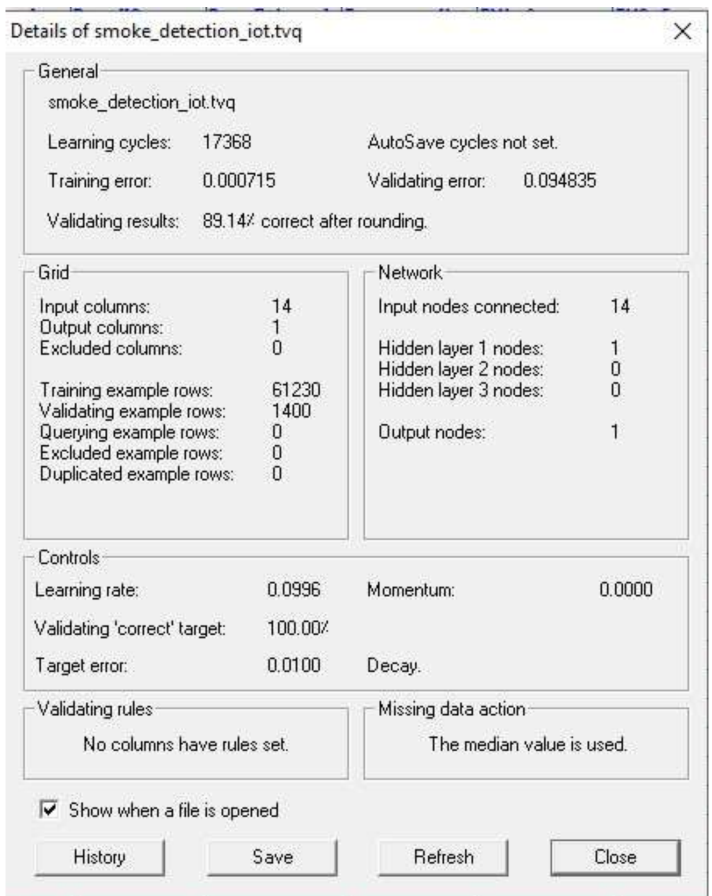

Figure 6: Details of the proposed ANN model

6. Conclusion:

a) In this study, we embarked on a journey to address the critical issue of predicting smoke potential in a specific geographical area, leveraging the power of neural networks and a comprehensive dataset. Our investigation has yielded valuable insights and contributions to the field of air quality forecasting and environmental stewardship.

b) Our neural network model, consisting of five layers and trained on 15 environmental features, has proven its efficacy in predicting smoke potential, achieving an impressive accuracy of 89.14% and an average error of 0.000715. This level of performance demonstrates the model's potential to provide timely and accurate predictions, thereby empowering decision-makers and communities to take proactive measures in mitigating the impact of smoke events on public health and the environment.

c) One of the significant outcomes of our research is the identification of influential environmental features. Temperature, humidity, crude ethanol, pressure, NC1.0, NC2.5, SCNT, and PM2.5 have been pinpointed as key factors contributing to smoke occurrence. Understanding the role of these variables not only enhances the predictive power of our model but also offers actionable knowledge for crafting targeted mitigation and preparedness strategies.

d) While our study represents a significant step forward in smoke prediction, it is not without limitations. We acknowledge the importance of ongoing research to address challenges related to data quality, regional variability, and real-time implementation. Future endeavors might explore the integration of additional data sources and more sophisticated neural network architectures to further enhance predictive accuracy.

In conclusion, our research underscores the potential of data-driven approaches and neural network modeling in addressing complex environmental challenges. The ability to predict smoke potential with precision holds promise for public health protection, environmental management, and community well-being. As we continue to refine and expand our predictive capabilities, we move closer to a future where timely and informed decisions can minimize the impact of smoke events, fostering safer and healthier communities.

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