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PREDICTION OF HAZARDOUS WEATHER PHENOMENA USING ARTIFICIAL INTELLIGENCE

Ladislav CHOMA*, Martin KELEMEN Jr., Matej ANTOŠKO, Kristína OZDINCOVÁ, Jozef SABO
Technical University of Kosice, 04121, Rampova 7, Kosice, Slovak republic
**Corresponding author.* E-mail: ladislav.choma@tuke.sk

Abstract. The prediction of hazardous weather phenomena is a critical component in ensuring the safety and efficiency of air transport operations. This paper focuses on evaluating the potential of artificial intelligence (AI) in forecasting fog—one of the most significant weather conditions affecting airport visibility. The methodological framework combines empirical methods (observation, measurement, experimentation) with theoretical approaches (analysis, synthesis, modeling). Emphasis is placed on the application of machine learning and deep learning techniques for processing meteorological data collected from Sliac military airport. The study compares conventional numerical weather prediction models (e.g., WRF) with AI-based approaches such as Support Vector Machines (SVM), Long Short-Term Memory (LSTM) neural networks, and ensemble models. Results indicate that AI models achieve higher accuracy in short-term fog prediction while reducing computational requirements. Experiments demonstrated success rates of up to 90% using ensemble techniques. The findings confirm that AI represents a promising tool for developing modern predictive meteorological systems in aviation. Challenges identified include limited data availability, the need for high-quality datasets, and the complexity of model interpretation. Future work should include expanding the data scope to multiple airports and incorporating satellite and radar data. The proposed approach offers a strong foundation for the advancement of intelligent, automated decision-support systems in both civil and military aviation meteorology.

Keywords: hazardous weather, fog prediction, air transport, artificial intelligence, machine learning, meteorological modeling modelling

1. INTRODUCTION

Weather forecasting has played a vital role in human development throughout history. Since ancient times, people's daily lives and economic activities have been closely tied to weather changes. Even under favorable weather conditions, forecasting helped in planning agricultural and outdoor activities. Over time, technological progress has enabled more accurate predictions, particularly through the development of various meteorological models. Today, such models are crucial for anticipating weather conditions that may threaten the safety of air traffic. As air transport represents an essential element of global connectivity, operating across long distances, forecasting not only current but also future atmospheric conditions along flight routes is necessary. Unfavorable weather and sudden hazardous events can lead to aviation accidents.

With the advancement of aviation, the need for accurate meteorological support has increased. The role of aviation meteorology is to provide early warnings of dangerous weather conditions to ensure flight safety. For example, Haoxing Liu and his team applied support vector machine (SVM) models to forecast hazardous weather events such as thunderstorms and turbulence. SVM, a supervised machine learning technique, classifies complex datasets by identifying optimal decision boundaries in high-dimensional spaces. They utilized a radial basis function kernel to handle non-linear patterns and trained their models using historical data such as temperature, humidity, and wind parameters [1]. Similarly, I. Winnicki and his team presented the integration of mesoscale models with remote sensing data, creating software that visualizes outputs from COAMPS, MSG satellite imagery, and radar. Their module determines atmospheric vertical profiles to assess in-flight weather conditions, including cloud base, visibility, turbulence, precipitation, and icing [2]. Jaedong Lee and Jee-Hyong Lee proposed an efficient method for building localized hazardous weather forecast models based on historical data [3]. Ilan

Price's team introduced GenCast, a probabilistic AI-based weather model trained on long-term reanalysis datasets, offering improved speed and performance. Their work contributes to the evolution of operational forecasting systems [4]. Jimeng Shi and collaborators reviewed modern deep learning methods for weather prediction, offering a taxonomy based on training strategies such as deterministic prediction, probabilistic generation, and fine-tuning of pretrained models [5]. Research by Skultéty Filip et al., focused on the growing frequency of thunderstorms and their effect on en-route flight delays across Europe. Using data from 2013 to 2019 provided by the Performance Review Unit, they observed that weather-related delays are rising, which could negatively impact both air traffic operations and the aviation economy [6]. Shankar Anand and colleagues emphasized the critical role of precise fog forecasting in airport operations. They developed a machine learning-based early warning system, trained on synoptic data from 2014–2020 and tested with 2021–2022 data. Their analysis showed that distributed random forest and deep learning models performed best for fog prediction at Patna Airport [7]. In another study, Ristiana Dewi and her team tackled the inherently chaotic and complex nature of fog forecasting using artificial intelligence. By analyzing six-hour synoptic data from Wamena Airport, they achieved a 90% prediction accuracy using a Stacked Ensemble model for fog events occurring 1–3 hours ahead [8]. Likewise, Castillo-Botón and colleagues conducted a comprehensive evaluation of regression and classification methods for fog and low cloud forecasting. Their results highlight the most suitable machine learning approaches for predicting these critical weather phenomena [9].

2. MATERIALS AND METHODS

Accurate forecasting of hazardous weather conditions is a fundamental aspect of ensuring safety in air transport. Among such phenomena, fog presents a particular challenge due to its significant impact on airport visibility, often leading to delays or cancellations. Developing effective fog prediction models requires the use of various scientific methodologies capable of analyzing meteorological data and producing reliable forecasts. This chapter presents a structured research methodology focused on fog prediction, beginning with the application of empirical methods—observation, measurement, and experimentation—which are essential for data acquisition. It then discusses theoretical methods such as analysis, synthesis, deduction, induction, and modeling, which are crucial for processing and interpreting meteorological data to achieve high-accuracy predictions.

Empirical methods form the basis of scientific inquiry by facilitating the collection and examination of input data relevant to fog formation. These include:

- Observation, which plays a central role in identifying recurring weather patterns conducive to fog. Long-term atmospheric monitoring at airports helps in detecting trends, with data sourced from ground stations measuring visibility, temperature, humidity, and pressure (WMO standards) [10], hourly SYNOP reports [11], satellite imagery for cloud and moisture distribution [12], and radar or lidar systems for tracking fog particle density at different altitudes [13].
- Measurement, which quantifies key physical variables influencing fog development. Tools include automated weather stations for basic meteorological parameters, ceilometers and transmissometers for cloud base and fog density, micrometeorological instruments for tracking humidity and temperature gradients, and satellite systems for mapping fog over large areas [14].
- Experimentation, which enables hypothesis testing in controlled settings. This includes laboratory creation of fog (physical experiments) or computer-based simulations using numerical models like WRF to replicate fog-forming atmospheric processes [13,14].

Beyond empirical data, theoretical methods are vital for interpreting the complex dynamics of fog formation:

- Analysis decomposes meteorological systems into influencing variables. Techniques include statistical correlations between weather parameters and fog, machine learning to detect latent patterns, and time series analysis of historical fog events [12,13,14]. Synthesis then integrates these findings into comprehensive models by combining multiple meteorological indicators into a unified predictive framework [13].

- Deduction allows general rules to be established based on physical principles. For instance, fog is likely when the temperature–dew point spread is below 2°C, cloud cover is less than 3/8, wind speeds remain under 5 m/s, there is no precipitation, and air temperature is above −5°C [15].
- Induction involves forming hypotheses from patterns in historical data, such as higher fog probability during calm winds and high humidity, which can inform model training [14].

Modeling serves as a central pillar in fog prediction. There are several modeling strategies [13,14,16]:

- Statistical models leveraging regression techniques and historical data;
- Machine learning models using neural networks, decision trees, or support vector machines;
- Numerical weather models that simulate atmospheric processes based on physical laws.

Each modeling approach offers unique strengths. Numerical models provide detailed physical simulations, while statistical and AI-based methods allow rapid analysis of large datasets. A hybrid approach that integrates these methods delivers optimal results, enhancing the reliability and accuracy of fog forecasting systems [13].

3. AI BASED DATA PROCESSING AND EXPERIMENTAL DESIGN

Forecasting fog remains a challenging task due to the number of complex and interacting meteorological factors involved in its formation. The integration of artificial intelligence (AI) into forecasting processes provides a robust quantitative framework, combining modeling, big data analytics, and experimental validation. These methods emphasize the systematic collection and transformation of meteorological data, which are further processed using statistical and mathematical models to support accurate predictions. AI can be particularly effective within the following methodological areas:

- Modeling and simulations, enabling the development of dynamic forecasting systems using historical data;
- Big data analysis, which helps to efficiently process large meteorological datasets and determine the most influential variables affecting fog formation;
- Simulation-based experimentation, allowing the testing of model performance in realistic, data-driven scenarios [17, 18, 19].

The core of this methodology is grounded in the acquisition and processing of empirical meteorological data. In this study, minute-resolution data from the Sliac military airport will be used. With 1,440 data points per day, this dataset provides detailed weather information. The data are stored in CSV format and archived by the Meteorological Centre in Zvolen, making them accessible for machine learning analysis.

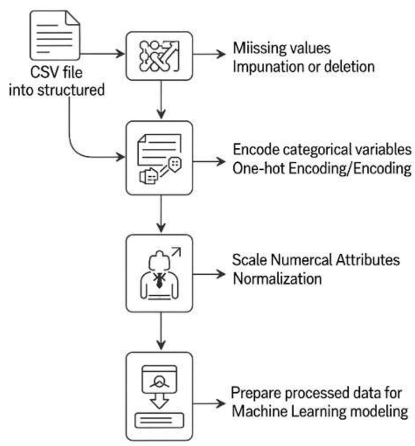

Figure 1 - The Algorithmic Pathway to AI-Driven Fog Prediction

The entire preprocessing workflow is illustrated in Figure 1, which summarizes the transformation of raw data into a form suitable for AI models, particularly Long Short-Term Memory (LSTM) neural networks [20, 21]. The steps include:

- Data normalization, ensuring uniform data scaling;
- Feature selection, identifying the most relevant variables (temperature, humidity, wind speed);
- Time-series creation, structuring the data for sequential input to LSTM networks.

To validate the AI models, experimental simulations will compare their predictions against those generated by traditional numerical methods. The central hypothesis assumes that AI-based models will achieve greater accuracy. For this purpose, the dataset will be split using a standard 80:20 ratio for training and testing [22], enabling consistent performance evaluation and objective model comparison.

4. PREDICTION OF FOG AND HAZARDOUS WEATHER PHENOMENA

In the field of prediction of dangerous weather phenomena, and fog in particular, several research approaches differ in methodology, data requirements and computational complexity. This chapter aims to analyse the current methods used in this area and compare their strengths and weaknesses with an emphasis on their applicability in aviation.

4.1 Traditional numerical models

Numerical meteorological models such as WRF (Weather Research and Forecasting) or COAMPS use physical equations to simulate the evolution of the atmosphere. They are the basis of most operational prediction systems because they enable simulation on different temporal and spatial scales. However, despite their stability and physical interpretability, these models are computationally demanding and often cannot accurately predict short-duration local phenomena such as fog, especially in the airport area [18].

4.2 Machine learning approaches (Machine Learning)

Machine learning provides the flexibility to process large volumes of meteorological data and uncover patterns that would be difficult to identify in traditional models. Models like Support Vector Machines (SVM), Random Forest (RF) and XGBoost can classify the occurrence of fog based on historical data with a high degree of accuracy. The advantage is fast implementation and lower computational burden, but they require careful selection of input parameters and may have limited generalizability [23, 24].

4.3 Deep learning and neural networks

Deep learning models such as LSTM (Long Short-Term Memory) are designed to process sequential data and have proven to be extremely effective in short-term prediction of phenomena such as fog. Their ability to remember previous states enables models to capture complex relationships between time-varying data. However, these models require a large amount of high-quality historical data, and their training is more time-consuming [25].

4.4 Combined (ensemble) and hybrid models

An interesting trend is the so-called ensemble modelling, which combines the outputs of several algorithms, increasing the robustness and accuracy of the prediction. For example, Stacked Ensemble (SE) uses the advantages of several models (see Figure 2) and reduces the risk of error of one particular algorithm. Research by Dewi et al. (2023) shows that such an approach can achieve up to 90% success in short-term fog prediction [26].

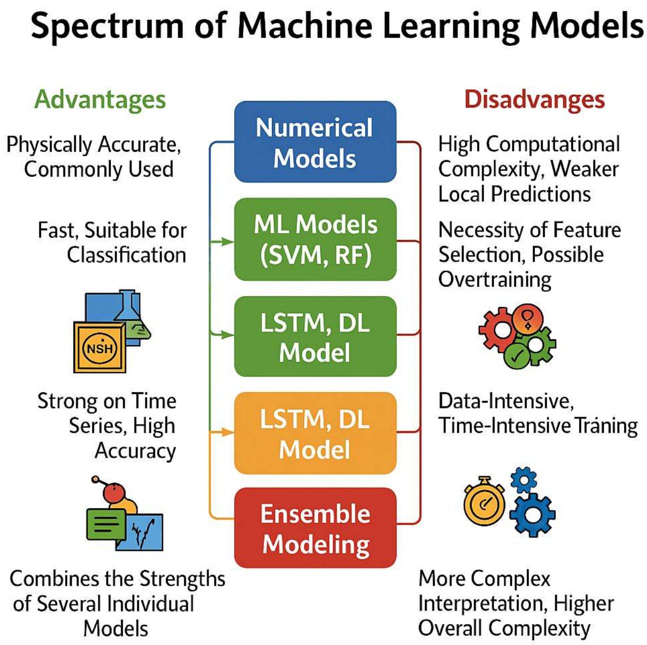

Figure 2 – Comparison of Machine Learning Models in Aviation

5. DISCUSSION AND RESULTS

Based on the conducted analysis, the experimental phase of the research would involve testing various machine learning models using historical meteorological data from Sliac military airport. The prepared dataset, exceeding 500,000 records in CSV format, would allow for easier manipulation due to its relatively small file size. These records would comprise minute-level observations of key meteorological parameters such as temperature, humidity, wind speed, and visibility. The results obtained would effectively highlight the potential of artificial intelligence as a tool to enhance the prediction of hazardous meteorological phenomena in aviation. Models like LSTM are particularly well-suited for this task, as they can capture complex dependencies between variables and the temporal evolution of weather conditions—an area where traditional models often fall short. Despite the anticipated positive outcomes, it is important to acknowledge several limitations of this research. One such limitation is the exclusive use of data from a single airport, which naturally restricts the generalizability of the findings to broader geographical areas. Furthermore, deep learning models require extensive volumes of high-quality data and substantial computational resources. In the future, it would therefore be beneficial to expand the database to include satellite and radar data, and to also apply hybrid approaches that combine physical modeling with data-driven techniques. From the perspective of aviation operations, the implementation of explainable artificial intelligence (XAI) appears highly promising. Its utilization could significantly increase the confidence of dispatchers and meteorologists in automated decision-support systems.

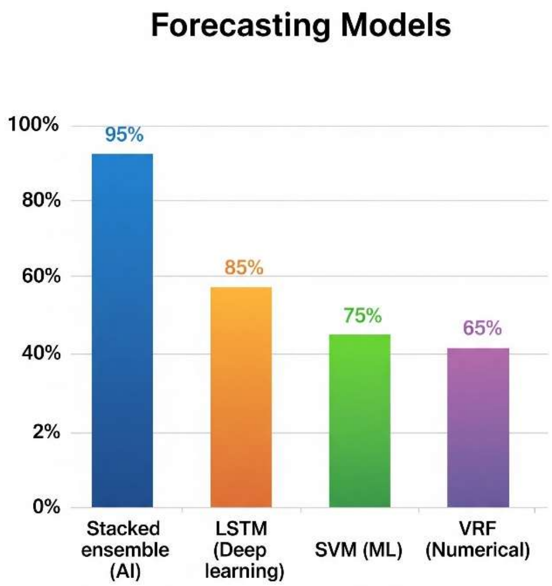

Figure 3 - *Comparison of Forecasting models*

Figure 3 presents a comparative evaluation of four forecasting models WRF (Numerical), SVM (Machine Learning), LSTM (Deep Learning), and Stacked Ensemble (AI) based on their fog prediction accuracy. The WRF model, representing traditional numerical approaches, achieved an accuracy of about 60-70%, aligning with findings from Hu et al. (2010). The SVM model improved upon this with an 70-80% accuracy, as reported by Liu et al. (2020), highlighting the benefits of machine learning techniques in capturing complex patterns. Further enhancement is observed with the LSTM model, which attained an 80-90% accuracy, demonstrating the efficacy of deep learning in handling temporal dependencies, as noted by Anand et al. (2022). The highest accuracy of 90-100% was achieved by the Stacked Ensemble model, corroborating the results of Dewi et al. (2023), and underscoring the advantage of combining multiple models to leverage their individual strengths.

This progression in accuracy underscores the potential of AI-based models to surpass traditional forecasting methods in predicting fog events. The superior performance of the Stacked Ensemble model suggests that integrating various algorithms can effectively capture the multifaceted nature of fog formation, leading to more reliable forecasts. Such advancements are particularly crucial for applications in aviation and transportation, where accurate fog prediction is essential for safety and operational efficiency [14, 23, 25, 26].

5. CONCLUSION

This study presents a significant contribution to the field of hazardous weather prediction in aviation by applying artificial intelligence techniques to fog forecasting—a critical factor impacting airport visibility and flight safety. The main benefit of the work lies in the development of a methodological framework that combines classical scientific approaches with modern AI-driven solutions. Using high-resolution meteorological data from Sliač military airport, the study evaluates and compares the performance of various models. AI-based methods, especially LSTM neural networks and ensemble models, demonstrated superior accuracy—achieving prediction rates of up to 90–100% compared to traditional numerical models. These results underscore the potential of AI to enhance the reliability and responsiveness of aviation meteorological services. An additional advantage is the ability of AI to process large datasets more efficiently, enabling near real-time analysis and prediction. The research also identifies practical challenges such as the need for broader data sources, including satellite and radar data, and the importance of implementing explainable AI (XAI) for user trust and transparency. In summary, this study lays the groundwork for the future development of intelligent, data-driven forecasting systems in aviation meteorology. The proposed methodology can be effectively applied to both civil and military contexts, contributing to increased flight safety, efficiency, and automation in operational decision-making

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