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# Forecasting Short-Term Wind Speed using ARIMA, and Convolution Neural Network Models at International Airports in Saudi Arabia

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**Abstract:**

This study aimed to predict the maximum wind speed (MWS) at three international airports of Saudi Arabia, such as King Abdulaziz International Airport (KAIA), King Fahd International Airport (KFIA), and King Khalid International Airport (KKIA). For this end, we utilized advanced machine learning (ML) and Statistical techniques, including Artificial Neural Network (ANN), Convolution Neural Network (CNN), and Autoregressive Integrated Moving Average (ARIMA) models, and the daily maximum wind speed data during 2021-2023. To develop the models, we effectively employed the average mutual information (AMI) for assessing the suitable input variables to predict the maximum wind speed in KKIA, KFIA, and KAIA. The MWS forecasting models of three airports were constructed using the training subset (80%, spanning from 2021 to 2023 May) and testing subset (20%, between 2023 May and 2023 Dec). The results showed that the accuracy of the findings has been improved by implementing the proposed CNN models. Compared to the ANN, and ARIMA models, the CNN algorithm showed its remarkable potential as a high-level model in accurately estimating KKIA, KFIA, and KAIA max wind speed values and exhibiting superior generalization capability and minimal variance.

**Keywords:** Convolution Neural Network, Airport wind speed, forecasting, Statistical model.

## 1. Introduction

The wind is vital in determining weather conditions within the aviation sector (Naskar et al., 2023). Predicting wind speed accurately is challenging due to its sporadic and unstable nature. The lack of sufficient data and relevant research on wind speed at Entebbe International Airport is an additional obstacle impeding the airport's progress toward sustainable development (Wesonga et al., 2019). Airports typically reside in expansive territories, boasting specific wind patterns advantageous for aerial movements. To guarantee safe flights and efficient planning, it is crucial to have access to reliable weather data and forecasting tools due to the impact of wind speed and direction on aircraft performance, fuel consumption, range, and passenger comfort. For flight operations and safety, wind speed and direction play a crucial role as aircraft rely on headwinds and tailwinds for successful takeoff and landing (Naskar et al., 2023). Wind speeds higher than 34 kilometers per hour can cause harm to small aircraft (WMO Technical Regulations, 2013).


Machine learning deals with the challenge of constructing computers that can autonomously enhance their performance through accumulated experience (Jordan & Mitchell., 2015). Through the high-performance computing and synergy of big data technologies, machine learning has revolutionized data-intensive science in multi-disciplinary technologies (Liakos et al., 2018). Wind speed prediction through machine learning has gained considerable significance in recent times, owing to its ability to enhance the accuracy of wind energy production and provide valuable insights into climate events in airports (Alves et al., 2023). Using machine learning for wind speed prediction offers numerous advantages, such as Improved accuracy, Short-term forecasting, and Adaptability (Lagomarsino et al., 2023; Kumar., 2019). The non-parametric ML models effectively evaluate nonlinear relationships between input and output variables. The successful examination of wind Speed has been achieved through the implementation of multiple standalone ML models like support vector machine (SVM), artificial neural networks (ANN), Convolution neural networks (CNN), adaptive neuro-fuzzy inference systems (ANFIS), LSTM deep learning, RF, LR, and extreme learning machines (Lawal et al., 2021; Demolli et al., 2019; Chitsazan et al., 2019; Chen et al., 2018; Liu et al., 2014; Kavasseri and Seetharaman, 2009).

Analytical models used to make statistical projections include linear regression (LR), time series forecasting (TSF), classification and regression trees (CART), simple moving average (SMA), exponential smoothing (SES), autoregressive integrated moving average (ARIMA), and seasonal are autoregressive integrated moving average (SARIMA). The diverse range of models available offer unique strategies for forecasting future trends through analysis of historical data and consideration of specific event needs. Also, many studies have been done with statistical methods to predict the time series of meteorological events, in which the statistical models have performed somewhat acceptable (Elsaraiti and Merabet, 2021; Yatiyana et al., 2017; Lydia et al., 2016).

According to previous studies, less research has been done in the field of aviation, especially airports, with advanced CNN models. Consequently, this endeavor examines the effectiveness of ARIMA, ANN, and CNN models in precisely predicting the airports' highest wind velocity. To date, no studies have been reported in forecasting Max Wind Speed for King Khalid International Airport fluctuations using the CNN technique.

## 2. Materials and Methods

### 2.1. Study area and data required

In this study, three international airports in Saudi Arabia were selected to forecast multistep maximum wind speed (MWS) are (**Fig. 1**).

- King Khalid International Airport (KKIA), which is situated 35 kilometers north of Riyadh, lying between 24°57′28″N, 46°41′56″E latitude and 24°95′78″N, 46°69′89″E longitude and 625 m above sea level (Almuharib., 2014). As a significant airport in Riyadh, Saudi Arabia, King Khalid International Airport functions as a central hub for numerous flights with origins in both the domestic and international sectors. KKIA covers an area of 105 square kilometers (41 square miles) and has a hot desert climate with long, sweltering summers and cool, dry winters. From January to July, there is a yearly temperature range spanning from 43°F to 110°F, with July experiencing the highest temperatures and January being the coldest month.

- King Fahd International Airport which is named after the former King of Saudi Arabia, Fahd ibn Abdulaziz, is located 31 kilometers northwest of downtown Dammam. Lying between 26°29′32″N, 49°48'87″E latitude and 24°95'78″N, 46°69'89″E longitude and 22 m above sea level (Salama et al., 2016). Situated in the Eastern Province of Saudi Arabia, it is the largest airport and remains one of the busiest in the country. At King Fahd International Airport, the weather is characterized by hot summers and mild winters due to its desert climate. The airport average temperature fluctuates occasionally, falling within a range of 16°C to 28°C. Typically, the wind velocity at the airport is moderate, reaching an average speed of 11 km/h.

- King Abdulaziz International Airport (KAIA), located in Jeddah, Saudi Arabia, acts as the entryway for Hajj and Umrah pilgrims on their journey to the Holy Mosque in Mecca. lying between 21°40′46″N, 39°09′24″E latitude and 21°67′94″N, 39°15′67″E longitude and 15 m above sea level (Wali et al., 2021). In Jeddah, there is a hot desert climate marked by temperatures ranging from 16°C to 28°C, occasional shifts in weather patterns, and scarce rainfall. In terms of wind speed, June holds the title for being the windiest month with an average of 23.4 km/h; on the other hand, October takes the crown for being the calmest month with an average wind speed of 16.3 km/h.

For developing the models, we divided the MWS data sets into two parts: 80% for training (2021 to 2023 May) and 20% for testing (2023 May to 2023 Dec).


**Fig. 1** Study region King Khalid, King Fahd, and King Abdulaziz International Airports

In this research, we selected International Airports King Khalid, King Fahd, and King for evaluating the developed models implementing daily MWS data with low and high variations. The wind speed records from the year 2021 to 2023 at these airports were acquired from the Mathematica Database. Table 1 displays the statistical measures of the collected MWS data for KKIA, KFIA, and KAIA, exposing dissimilarity in their statistical characteristics. In **Fig. 2**, the daily MWS values measured can be seen across 2021-2023.

**Table 1.** Statistical characteristics of data

| Station | Statistical characteristics | Max Wind Speed (km/h) |
|---|---|---|
| King Khalid Airport | Min | 5.37 |
| | Median | 18.33 |
| | Max | 51.86 |
| | Mean | 19.09875 |
| | Variance | 50.70102 |
| | Skewness | 0.806569 |
| | Count | 1088 |
| King Fahd Airport | Min | 5.37 |
| | Median | 24.08 |
| | Max | 62.97 |
| | Mean | 26.31383 |
| | Variance | 76.25674 |
| | Skewness | 0.780272 |
| | Count | 1088 |
| King Abdulaziz Airport | Min | 5.37 |
| | Median | 22.22 |
| | Max | 61.12 |
| | Mean | 23.43877 |
| | Variance | 36.48064 |
| | Skewness | 1.010757 |
| | Count | 1088 |

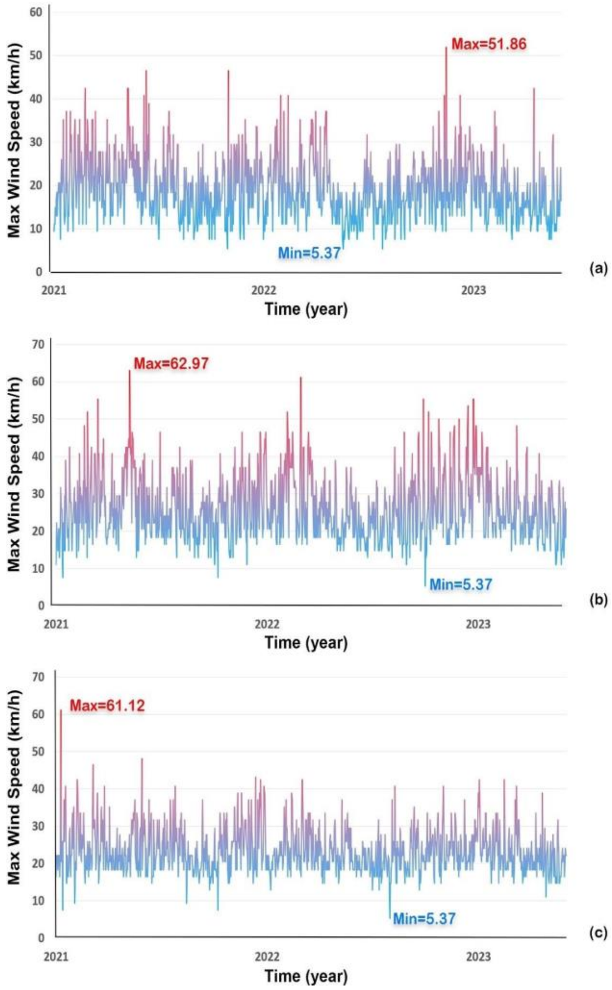


**Fig. 2** Daily max wind speed values in the KKIA (a), KFIA (b), and KAIA (c) period of 2021-2023

### 2.2. Selection of artificial intelligence time series forecasting model

#### 2.2.1. Artificial Neural Network (ANN)

One of the supervised machine learning models, ANN, falls under the category of artificial intelligence. Artificial neural networks have been created to generalize mathematical models of biological nervous systems and the advent of simplified neurons by McCulloch and Pitts (1943) sparked the initial fascination with neural networks (Abraham., 2005). The brain serves as the inspiration for these computer-based problem-solving tools, known as biological neural networks (Tran et al., 2021). ANNs are particularly well suited for tackling complex, real-world issues like comprehending climate due to their capacity to generate non-linear mappings during training (Elsner & Tsonis, 1992). In an ANN model, there are three layers: the input layer, hidden layer, and output layer. Neurons within each layer are connected to all neurons in other layers. ANNs possess the capability to adjust to shifting data patterns and acquire new information, thereby making them highly appropriate for dynamic forecasting environments and can handle noisy or incomplete data more effectively than traditional models, leading to more reliable forecasts (Wu & Feng, 2018; Zhang et al., 1998). The representation of the relationship between input (x) and output (Y) in an ANN is demonstrated by:

$$Y = f(W_1X_1 + W_2X_2 + \cdots + W_n + b) \quad (1)$$

The action function is denoted by $f$, with $b$ representing the bias and $W_i$ standing for the weight of the link. The structure of an ANN model is shown in Fig. 3.

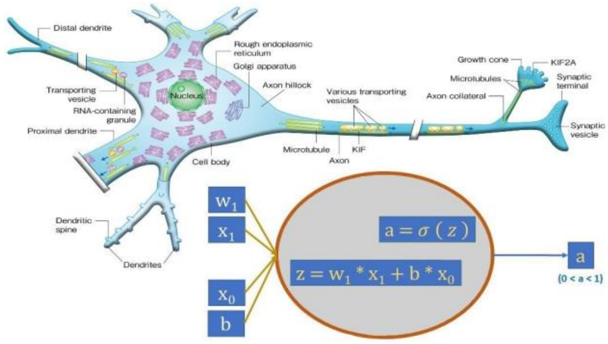


**Fig. 3** presents the structure of a common ANN model and biological neuron

### 2.2.2. Convolution Neural Network (CNN)

The network structures of convolutional neural networks (CNNs) are more intricate, granting them more powerful abilities in terms of feature learning and representation compared to traditional machine learning methods (Krizhevsky et al., 2012). CNNs acquire feature engineering autonomously using filters or kernels and are composed of several layers, including the input layer, convolutional layer, fully connected layers, and pooling layer (Emmert-Streib et al., 2020). The pooling layer is placed between successive convolutional layers, serving the purpose of data and parameter compression to mitigate overfitting and in most cases, the fully connected layer resides at the latter part of the convolutional neural network, exhibiting similarities to the connections found in traditional neural network neurons (Fukushima et al., 1980). The structure of a CNN model is presented in **Fig. 4**.

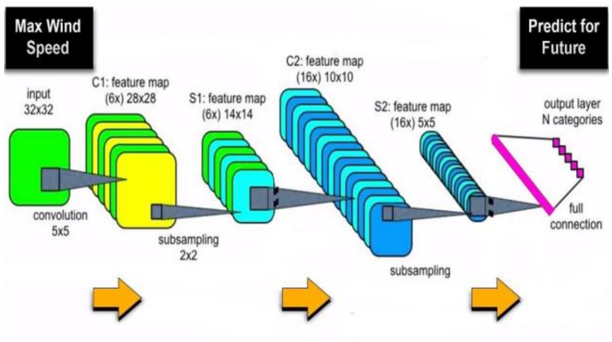


**Fig. 4** Different layers of convolutional neural network for prediction

CNN has the advantage of utilizing a shared convolution kernel, which effectively processes high-dimensional data, automatically extracts advanced features, and reduces the need for manual feature engineering (Krizhevsky et al., 2012), ultimately improving the accuracy of predicting maximum wind speed. The flowchart in **Fig 5** demonstrates the sequence of actions involved in creating and executing the ANN and CNN models.

### 2.3. Selection of a statistical time series forecasting model

#### 2.3.1. ARIMA model

The Autoregressive Integrated Moving Average (ARIMA) model is renowned for its effectiveness in time series analysis and forecasting tasks. An effective method for modeling and forecasting time series data with temporal correlation is the ARIMA model, commonly referred to as the Box- Jenkins method after its creators in 1970 (Box and Jenkins, 1970). By applying differencing techniques, ARIMA models can transform non-stationary data into stationary forms while removing trends and seasonality. In the AR component of the ARIMA model, the focused variable is regressed on its past values and the MA element within an ARIMA model highlights how the residuals are constructed by blending errors from past time intervals in a linear fashion (Dimri et al., 2020). The ARIMA(p,d,q) notation indicates the specific parameters of an ARIMA model.

$$y'_t = C + \phi_1 y'_{t-1} + \ldots + \phi_p y'_{t-p} + \theta_1 \varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-q} + \varepsilon_t \quad (2)$$

When d=1, the value of c remains unchanging and acts as the drift term in the equation. $\phi_1 y'_{t-1} + \ldots + \phi_p y'_{t-p}$ is the AR term having coefficients at order p from $\phi_1$ to $\phi_p$. $\theta_1 \varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-q}$ is the MA term with $\theta_1$ to $\theta_q$ as coefficients at q order, at each time point t, $\varepsilon_t$ is indicative of random noise from the background, whereas $y'_t$ stands for the differencing series. A view of this model is shown in **Fig. 5**.


**Fig. 5** Partial structural ARIMA model

### 2.4. Performance criteria

To analyze the performance of the developed models, the Coefficient of Correlation (R) and Root Mean Square Error (RMSE) performance metrics are utilized.

The RMSE is a statistical metric that calculates the mean of the square root of the discrepancy between the actual and anticipated values.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(MWS_{pi} - MWS_{oi})^2} \qquad 0 \leq RMSE \leq \infty \quad (3)$$

In prediction, correlation (R) serves as a statistical measure that quantifies how strong the relationship is between t wo variables.

$$R = \frac{\sum_{i=1}^{N}(MWS_{oi} - \overline{MWS_o})(MWS_{pi} - \overline{MWS_p})}{\sqrt{\sum_{i=1}^{N}(MWS_{oi} - \overline{MWS_o})^2 . \sum_{i=1}^{N}(MWS_{pi} - \overline{MWS_p})^2}} \qquad -1 \leq R \leq 1 \quad (4)$$

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where, $MWS_{oi}$ , $and$ $MWS_{pi}$ refer to observed and the predicted data, $N$ indicates the number of data, and $MWS_{OI}$ and $\overline{MWS}_{P}$ how the average of the observed and predicted data.

## 3. Results

### 3.1. Model development

Time series forecasting techniques can be classified as either univariate or multivariate, depending on the number of variables available for observation. To anticipate forthcoming MWSs, the univariate forecasting method was employed, assuming that future value of a time series is exclusively reliant on past value. This strategy offers certain benefits that surpass multivariate time series forecasting (Mirzania et al., 2023). The lower complexity of univariate time series forecasts generally results in faster estimation than their multivariate counterparts. It has been demonstrated in prior research (e.g., Iwok and Okpe, 2016; Castán-Lascorz et al., 2022) that the univariate forecasting models showed more accurate performance than multivariate models.

The effectiveness of a model can be significantly enhanced by carefully choosing the input variables in the field of modeling. When it comes to choosing the best input variables for the output variable, there are multiple approaches available, like Gamma Test, method of Average Mutual Information (AMI) (Ghorbani et al., 2022), and principal component analysis (Noori et al., 2011). In this study, an autocorrelation function was used to determine time delay $\tau$ value via the AMI technique. Indeed, the AMI method establishes how to join the time series $X(t)$ and the time series

$X(t + \tau)$ at a specific time t (Abarbanel, 1996). Optimal values for delay ($\tau$) at the airport can be determined by referring to **Fig. 6**, which demonstrates a correlation between the lowest AMI value and a delay of 3.

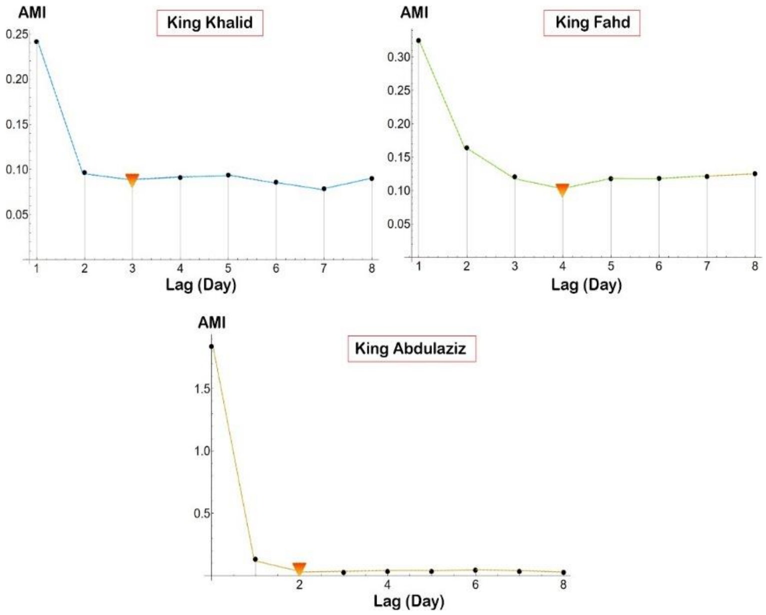


**Fig. 6** The Average Mutual Information for King Khalid, King Fahd, and King Abdulaziz Airport

Table 2 showcases distinct combinations of input variable(s) derived from the AMI outcomes to model airport MWS.

**Table 2.** The combinations of input variable(s) for multistep ahead wind max speed King Khalid, King Fahd, and King Abdulaziz Airport

| Airports | Scenario | Inputs | Output |
|---|---|---|---|
| King Khalid | M1 | MWS(t) | MWS(t) |
| | M2 | MWS(t), MWS(t-1) | MWS(t) |
| | M3 | MWS(t), MWS(t-1), MWS(t-2) | MWS(t) |
| | M4 | MWS(t), MWS(t-1), MWS(t-2), MWS(t-3) | MWS(t) |
| | M1 | MWS(t) | MWS(t) |
| | M2 | MWS(t), MWS(t-1) | MWS(t) |
| King Fahd | M3 | MWS(t), MWS(t-1), MWS(t-2) | MWS(t) |
| | M4 | MWS(t), MWS(t-1), MWS(t-2), MWS(t-3) | MWS(t) |
| | M5 | MWS(t), MWS(t-1), MWS(t-2), MWS(t-3), MWS(t-4) | MWS(t) |
| | M1 | MWS(t) | MWS(t) |
| King Abdulaziz | M2 | MWS(t), MWS(t-1) | MWS(t) |
| | M3 | MWS(t), MWS(t-1), MWS(t-2) | MWS(t) |

To identify the optimal input combination of maximum wind speed, Mathematica software was employed to determine the optimal parameters for the models during their training phase. Statistical and visual analysis were employed to assess the effectiveness of two standalone models (ANN and CNN) and one statistical model (ARIMA) in predicting MWS values. In Table 3, one can find the computed values of the performance criteria, such as coefficient of correlation (R) and RMSE, about testing periods. Moreover, the models' time series plots, scatter plots, and Violin plots are provided and presented in **Fig. 7-9** for King Khalid, King Fahd, and King Abdulaziz Airport during the testing period.

The findings from Table 3 reveal that within the realm of ANN models, the performance of ANN- M3 for King Khalid, ANN-M5 for King Fahd, and ANN-M3 for King Abdulaziz model proved to be good accurate during the testing phase. This is substantiated by its substantial R-value (0.992, 0.990, 0.979) and significantly reduced RMSE value (1.398, 1.241, 1.327), which were obtained through utilizing MWS(t), MWS(t-1), MWS(t-2) ... MWS(t-n) variables. Among the CNN models, CNN-M3 for all three airports model estimates values with less error based on the most value of R (0.997, 0.998, 0.995) and lowest value of RMSE (0.439, 0.516, 0.647) in the testing stage using MWS(t) variables. But ARIMA models, for respectively three airports estimate values with high error based on the lowest value of R (0.868, 0.861, 0.891) and highest value of RMSE (6.83, 8.95, 6.04) in the testing stage. The comparative analysis between the ARIMA, ANN, and CNN models reveals that the CNN model outperforms consistently in every input scenario (M1-Mn) from ANN and ARIMA models.

**Table 3.** Performance criteria of the three models in the testing periods for selected Airports

| **Airports** | **Testing** | | |
|---|---|---|---|
| | Model | R | RMSE (km/h) |
| | ARIMA | **0.8682** | **6.8341** |
| | ANN-M1 | 0.9877 | 1.4339 |
| | ANN-M2 | 0.9879 | 1.4724 |

| | | | |
|---|---|---|---|
| | ANN-M3 | **0.9920** | **1.3986** |
| | ANN-M4 | 0.9865 | 1.6015 |
| King Khalid | | | |
| | CNN-M1 | 0.9959 | 0.6398 |
| | CNN-M2 | 0.9960 | 0.6078 |
| | CNN-M3 | **0.9978** | **0.4391** |
| | CNN-M4 | 0.9973 | 0.4922 |
| | ARIMA | **0.8608** | **8.9500** |
| | ANN-M1 | 0.9894 | 1.4026 |
| | ANN-M2 | 0.9891 | 1.4626 |
| | ANN-M3 | 0.9827 | 2.2216 |
| | ANN-M4 | 0.9850 | 1.8700 |
| King Fahd | ANN-M5 | **0.9905** | **1.2413** |
| | CNN-M1 | 0.9966 | 0.7210 |
| | CNN-M2 | 0.9975 | 0.6809 |
| | CNN-M3 | **0.9984** | **0.5167** |
| | CNN-M4 | 0.9969 | 0.7236 |
| | CNN-M5 | 0.9971 | 0.7122 |
| | ARIMA | **0.8910** | **6.0443** |
| | ANN-M1 | 0.9689 | 1.4068 |
| King Abdulaziz | ANN-M2 | 0.9765 | 1.3920 |
| | ANN-M3 | **0.9797** | **1.3272** |
| | CNN-M1 | 0.9945 | 0.8976 |
| | CNN-M2 | 0.9952 | 0.7003 |
| | CNN-M3 | **0.9956** | **0.6476** |

In **Fig. 7**, we compared the time series graph of the best models of the ARIMA, ANN and CNN models (ARIMA, ANN-M3 and CNN-M3) for King Khalid, (ARIMA, ANN-M5 and CNN-M3) for King Fahd, and (ARIMA, ANN-M3 and CNN-M3) for King Abdulaziz airports. As shown in **Fig. 7**, the time series graphs of the CNN (M3) and ANN (M3 and M5) models indicate accurate performance and a noticeable similarity between them. Based on the scatter plots in **Fig. 8**, it can be observed that the CNN model demonstrates the highest level of precision ($R^2$ = 0.994, 0.996, 0.990), (RMSE = 0.439, 0.516, 0.647), whereas the ANN model displays a broader distribution of the measured and predicted MWSs ($R^2$ = 0.984, 0.98, 0.958), (RMSE = 1.398, 1.241, 1.327) and the ARIMA model displays a wider distribution compare two machine learning models ($R^2$ = 0.753, 0.741, 0.793), (RMSE = 6.83, 8.95, 6.04). In **Fig. 8**, it is seen that the relative errors for ANN models are situated within the range of -3 to 3, whereas for CNN models they lie between -

0.7 and 0.7 and ARIMA models are situated within the range of -20 to 20. Nevertheless, it is noteworthy that the majority of forecasted values in the CNN model have comparatively more miner relative errors than those in the ARIMA, and ANN models. The Violin plot in **Fig. 9** reveals that three models resemble each other and the observed values in terms of Violin shape.

Nonetheless, due to its minimal disparity, the CNN model stands out by closely resembling the Violin shape of the observed values.

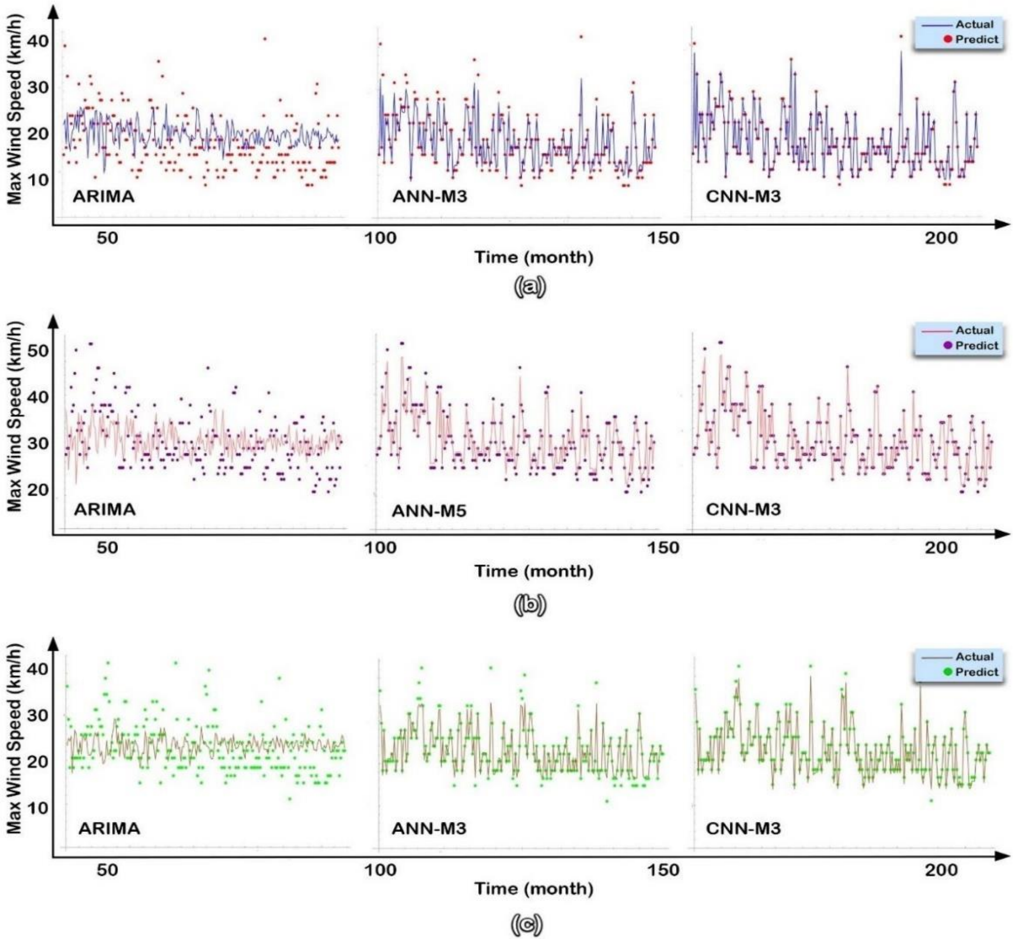


**Fig. 7** Time series for King Khalid (a) King Fahd(b), King Abdulaziz (c) airports of the observed and forecasted MWS(t) for the best ARIMA, ANN and CNN models at the testing stage

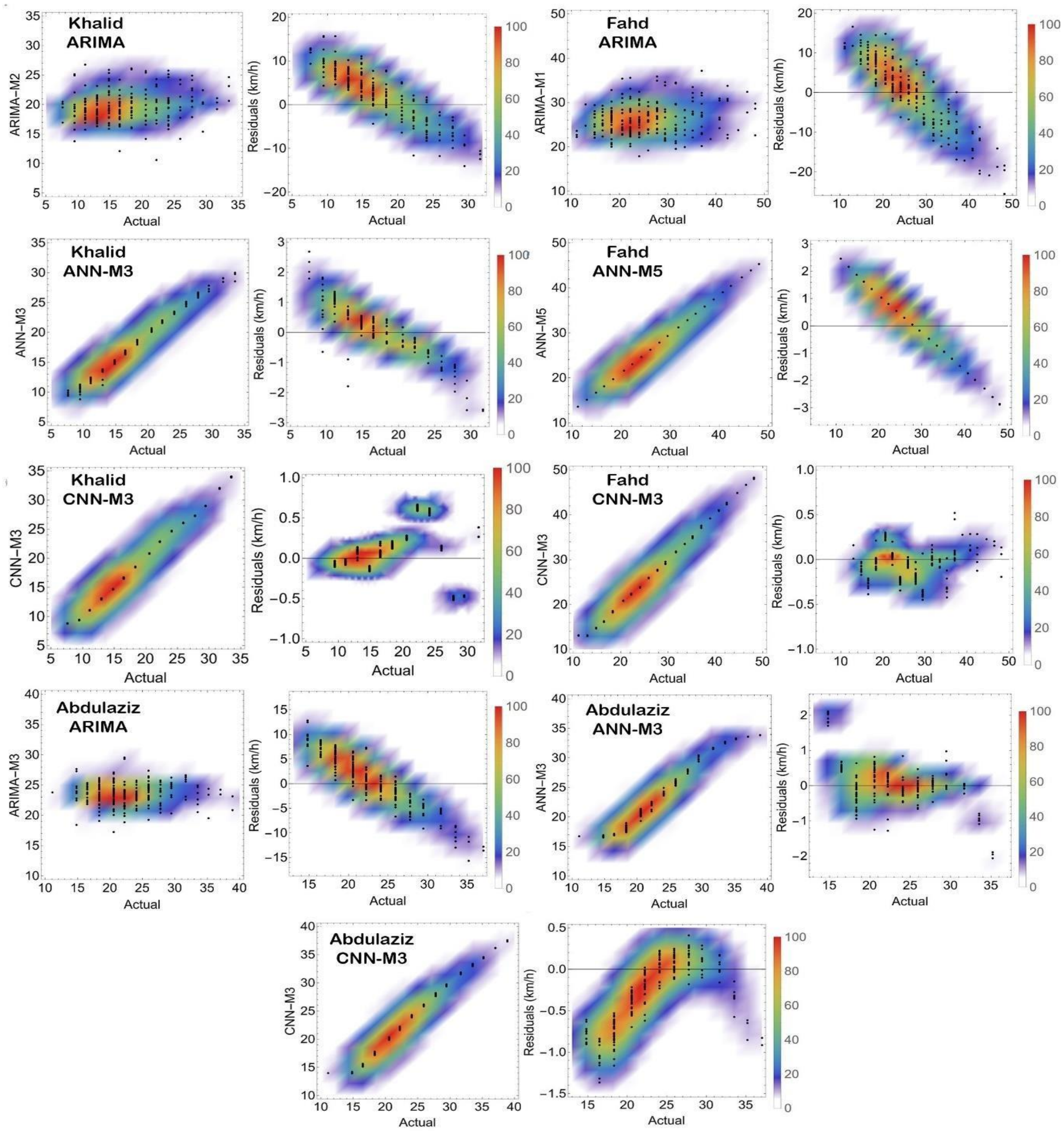


**Fig. 8** Scatter plot and relative errors for three selected airports of the observed and forecasted MWS(t) for the best ARIMA, ANN and CNN models at the testing stage

The violin diagram in **Fig. 9** shows that both CNN and ANN models have violin shapes similar to each other and similar to the observed sample. Also, the CNN-M3 model for all three airports performed better than the ANN-M3 models for KKIA, ANN-M5 for KFIA, and ANN-M3 for KAIA. Comparing the ARIMA model with the other two models, this model does not have an acceptable performance with very poor similarity. Hence, the Convolution Neural Network model is determined to possess superior capability in estimating MWS(t) at King Khalid, King Fahd, and King Abdulaziz International Airports compared to the Artificial Neural Network and Autoregressive Integrated Moving Average models. **Fig. 10,** the employed layers and modeling process associated with the superior scenario of both ANN and CNN models are illustrated.

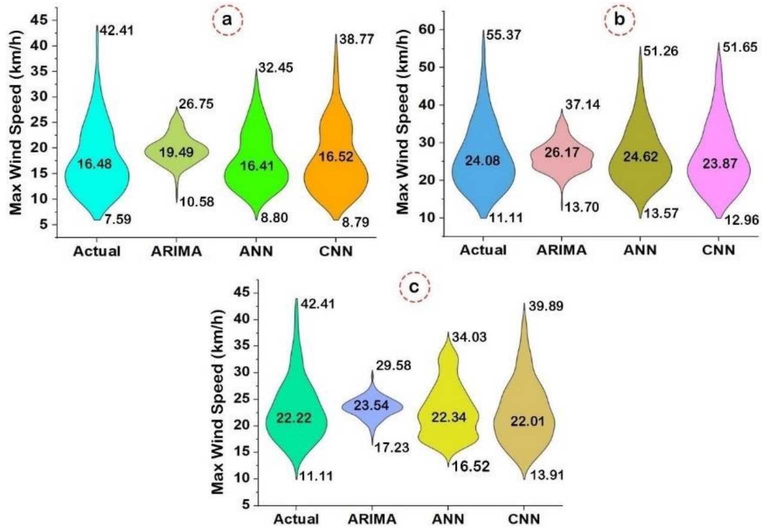


**Fig. 9** Violon plot for King Khalid (a) King Fahd(b), King Abdulaziz (c) airports of the observed and forecasted MWS(t) for the best three models at the testing stage

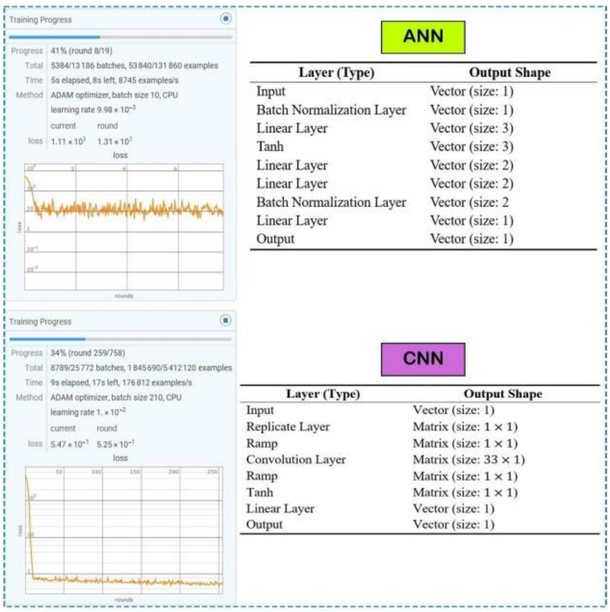


**Fig. 10** Modeling process of the observed and forecasted MWS(t) for the best ANN and CNN models

### 3.2. Discussion

The CNN model was effective in producing precise MWS predictions, particularly for the most extreme maximum values. Comparing the CNN model to the ANN, and ARIMA models in terms of statistical indicators and diverse graphical representations, it was observed that the CNN model exhibited superior performance in forecasting maximum wind speed in King Khalid, King Fahd, and King Abdulaziz International Airports. Increased precision and reduced variance are achieved in the CNN technique through the implementation of ensemble learning, thereby minimizing overfitting and enhancing model stability.

The accuracy of this study aligns with previous research (e.g., Lawal et al. 2021; Zhu et al. 2021; Fukuoka et al. 2018), wherein implementing a CNN model led to a substantial increase. It is worth mentioning that there hasn't been any investigation or evaluation of the use of the standalone CNN model in estimating the MWSs of KKIA, KFIA, and KAIA. Chiou et al (2012) used three extreme value models to investigate the maximum wind speed as an average of 10 minutes between 1951 and 1991 for the Italian airport. Naskar et al (2023), using a novel machine learning (ML) method, an effort was made to analyze the wind attributes of Netaji Subhas Chandra Bose International Airport (NSCBIA) and forecast wind velocity and direction 9, 30 hours in advance for the time span between 2016 and 2021. Arabi et al (2023) applied three machine learning models Long LSTM, CNN, and a network based solely on fully connected (FC) layers for retrieval ocean wind speed. Shen et al (2022) used LSTM and CNN models to predict multi-step wind speed, and concluded that based on the performance metrics the CNN-LSTM model outperformed the other implemented models. Lawal et al (2021) By utilizing CNN and a bidirectional long short-term memory (BLSTM) network, this strategy enables the reliable prediction of short-term wind levels at varying heights above ground level (AGL) in Saudi Arabia. They performance evaluation of the suggested CNN-BLTSM model involves using performance metrics namely RMSE, mean absolute error (MAE), and mean absolute percentage error (MAPE).

## 4. Conclusions

ML techniques are highly advantageous in accurately predicting nonlinear processes, particularly in the case of weather parameters like Wind speed, which is affected by factors such as rainfall and temperature, showing complex behavior. The present investigation focused on assessing the predictive capabilities of two ML models (ANN and CNN) and one stochastic model (ARIMA) in forecasting MWS(t) for King Khalid International Airport. To identify the most influential inputs among the different lag times, we utilized the AMI method. Considering statistical indicators like R and RMSE, as well as analyzing statistical graphs, an evaluation was performed to assess the performance of the three built models. The statistical data indicated that the three models developed for King Khalid Airport performed exceptionally well. Regarding predicting maximum wind speed, the CNN model outperformed the ANN, and ARIMA model by delivering superior results for KKIA. The CNN model, in simpler words, demonstrated exceptional forecasting capabilities by accurately generating MWS time series.

To improve the structure of intelligent standalone models, future research needs to focus on utilizing CNN and counterpart hybrid methods for predicting additional hydrological variables (e.g., visibility and wind direction variables), while also conducting comparisons with other algorithms. The achievement of successfully implementing a univariate model for King Khalid Airport MWS forecasting in this study implies the necessity of incorporating additional variables (such as visibility, temperature, and humidity) to develop a more comprehensive multivariate forecasting model for maximum wind speed.

*Author Contribution*: The author conceived the framework and structured the whole manuscript. The author has read and agreed to the published version of the manuscript.

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## Declarations

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