# AN ARTIFICIAL INTELLIGENCE APPROACH TO PREDICTION OF EXTREME EVENTS: THE CASE OF STORMS IN WESTERN FRANCE

Ayyoub Frifra[1,2], Mehdi Maanan[1], Hassan Rhinane[1] and Mohamed Maanan[2]

[1]Hassan II University of Casablanca, Geology Department, Faculty of Sciences Ain Chock, 20100 Casablanca, Morocco
[2]University of Nantes, UMR 6554 CNRS LETG-Nantes, Geography Institute, 44312 Nantes, France

**Commission 4, WG 7**

**KEY WORDS:** Storm prediction, Time series prediction, Deep learning, Machine learning, Gated recurrent unit, Support vector machines, Decision making.

## ABSTRACT

Storms represent an increased source of risk that affects human life, property, and the environment. Prediction of these events, however, is challenging due to their low frequency of occurrence. This paper proposed an artificial intelligence approach to address this challenge and predict storm characteristics and occurrence using a gated recurrent unit (GRU) neural network and a support vector machine (SVM). Historical weather and marine measurements collected from buoy data, as well as a database of storms containing all the extreme events that occurred in Brittany and Pays de la Loire regions, Western France, since 1996, were used. Firstly, GRU was used to predict the characteristics of storms (wind speed, pressure, humidity, temperature, and wave height). Then, SVM was introduced to identify storm-specific patterns and predict storm occurrence. The approach adopted leads to the prediction of storms and their characteristics, which could be used widely to reduce the awful consequences of these natural disasters by taking preventive measures.

## 1. INTRODUCTION

Extreme weather events, particularly storms, are one of the main natural hazards affecting human life, infrastructure, and the environment (Brunkard et al., 2008; Genovese & Przyluski, 2013; Jahn, 2015; Stephenson, 2008; Usbeck et al., 2010). It has been estimated that, on average, 60,000 people die each year due to extreme weather conditions (Franzke & Torelló i Sentelles, 2020). The economic losses from storms have also risen in most countries (Dorland et al., 1999; Kates, 1980; Leckebusch et al., 2007). However, storms are also important, as rain-bearing structures for large parts of the world; the case of West African parts that get 90% of their rainfall from thunderstorms (Kamara, 1986).

Due to the increased risk of these severe events (Haarsma, 2021; Kron et al., 2019), they have attracted significant attention in the last few decades (Ren et al., 2018). Predicting storms is a challenging task, and traditional prediction methods are mainly based on statistical and numerical models, leading to problems of high computational complexity and low prediction accuracy (Goerss, 2000). But machine and deep learning algorithms can rapidly analyze large volumes of data and serve as a cost-effective alternative for predicting upcoming events (Sun et al., 2020), such as impending hurricane trajectories and storms (Ghosh & Krishnamurti, 2018).

Recently, the application of machine learning and deep learning models dramatically increased in predicting natural hazards and disasters. For instance, flood prediction using machine learning models (Mosavi et al., 2018) or landslide susceptibility prediction using deep learning (Dao et al., 2020). The use of machine learning and deep learning models becomes more and more popular for the prediction of extreme weather events; deep learning models are currently used to forecast severe convective weather over China (Zhou et al., 2019), for example, and the prediction results prove that machine learning and deep learning solutions outperform traditional methods (Lu et al., 2020; Zhang

et al., 2019). (Sun et al., 2020) have also provided an overview of the current applications of these models in disaster management.

Gated recurrent unit (GRU) networks, which was developed as an improved version of recurrent neural networks (RNNs) to solve the problems of vanishing and exploding gradients in standard RNNs when learning long-term dependencies, is among the most advanced deep learning algorithms (Cho et al., 2014). The GRU model has outperformed other benchmark models and has shown to be effective for a wide range of issues, such as wave height prediction during tropical cyclones (Meng et al., 2021), wind power forecasting (Ding et al., 2019), and tropical cyclone track prediction (Lian et al., 2020).

In addition to GRU, support vector machines (SVM) is another robust and efficient machine learning algorithm widely used for time series classification and regression problems (Kampouraki et al., 2009; Sapankevych & Sankar, 2009). This algorithm has outperformed other methods in a wide variety of applications, such as extreme rainfall event prediction (Nayak & Ghosh, 2013), convective storms classification (Jergensen et al., 2020), flood prediction (Mosavi et al., 2018), and tornado Prediction (Trafalis et al., 2004).

This paper proposes a new approach for predicting the occurrence and characteristics of storms using buoy data and a storm database containing all storm events that occurred in Brittany and Pays de la Loire regions, Western France, since 1996. The GRU model was introduced to predict storm characteristics (wind speed, pressure, humidity, temperature, and wave height). The SVM model attempted to identify storm-specific patterns and applied an SVM-based classifier for storm occurrence prediction. The remainder of this paper is organized as follows. Section 2 covers the study area, the data used, the architectures of the proposed models, and the methodology adopted. Section 3 presents the results of the experiment. Finally, Section 4 discusses the conclusions and summarizes the paper.

## 2. EXPERIMENTS

### 2.1 Study Area

This study focuses on a portion of The French Atlantic coasts. It comprises two regions: Brittany and Pays de la Loire with a total area of 66000 km$^2$ (Figure 1).
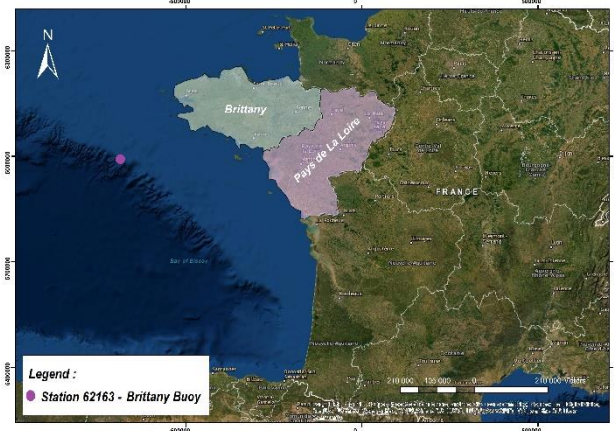


**Figure 1**. Location of the study area.

These two regions have known several storms leading to heavy loss of life and devastating infrastructure damage. Storms Lothar and Martin, for example, which hit the study area from December 26 to 28, 1999, caused the death of 92 people (Dedieu, 2010), in addition to the destructive impact on infrastructure, buildings and the environment (Sacré, 2002).

Due to the extensive damage and the risk represented by these extreme events, several works of literature have investigated the dynamics and paths of past storms affecting the study area; (Athimon & Maanan, 2018) studied storm impacts and vulnerability of past societies based on more than 19691 French historical documents, while other studies attempted to detect damaging storm events in the last 300 and 1000 years by coupling historical documents and sedimentological data (Pouzet et al., 2019; Pouzet & Maanan, 2020). These studies have identified two main categories of storms that affect the study area. The first type of storm has a west-to-east trajectory, and the second type has an SW-NE trajectory (Pouzet & Maanan, 2020).

### 2.2 Data Used

The data used is a combination of a storm database and buoy data. The storm database was obtained from the website Meteo France (http://tempetes.meteo.fr/spip.php?rubrique6), and it represents all the storm events that have occurred in the study area over the past 25 years.

The buoy data consists of data collected from station 62163 - Brittany Buoy, which contains records of wind speed, pressure, humidity, temperature, and wave height from January 1, 1996, through May 31, 2021. The buoy data was downloaded from the website Meteo France (https://donneespubliques.meteofrance.fr/?fond=produit&id_produit=95&id_rubrique=32).

The final time series data used to predict storm occurrence and characteristics represent daily records of wind speed, pressure, humidity, temperature, and wave height, in addition to the exact days that have known the occurrence of a storm.

### 2.3 Proposed Models: GRU and SVM

**2.3.1 Gated Recurrent Unit (GRU) neural network**: Recurrent neural networks (RNNs) are a powerful deep learning model known for their effectiveness in time series prediction (Elman, 1990). However, RNN faces problems when learning long-term dependencies due to the vanishing and exploding gradient problems (Bengio et al., 1994). To overcome these issues, Long Short-Term Memory (LSTM) was proposed in 1997 as an improved version of RNN (Hochreiter & Schmidhuber, 1997). Moreover, a gated recurrent unit (GRU) neural network was introduced by (Cho et al., 2014) to simplify the training parameters.

The architecture of GRU implements a restructuring gate mechanism while retaining the advantages of LSTM. The gate mechanism consists of an update gate and a reset gate. The update gate controls how much information from a previous state is brought into the current state. The more information brought into the current state, the higher the value of the update gate. It plays the role of input gate and forget gate in LSTM. On the other hand, the reset gate is used to control how much information from a previous state is ignored. In contrast to the update gate, the lower the reset gate value, the more information is ignored (E et al., 2019).

The processes inside each GRU cell are designed as follows (E et al., 2019):

First, the reset gate and update gate are established by the inputs of the current input $X_t$ and the hidden state at previous time $H_{t-1}$. The outputs of the update gate and the reset gate are given as follows:

$$r_t = \sigma(X_t U^r + H_{t-1} W^r + b^r \tag{1}$$

$$z_t = X_t U^z + H_{t-1} W^z + b^z \tag{2}$$

where      $U$ and $W$ = are weight coefficient matrices.
         $b$ = denotes bias vector.
         $\sigma$ = is the logistic sigmoid function.

$r_t$ helps to capture the short-term dependencies in temporal sequence, and $z_t$ is able to memorize arbitrary-length information of the input $X_t$.

Second, the current candidate hidden state $\widetilde{H}_t$ is formulated as:

$$\widetilde{H}_t = \tanh(X_t U^H + (H_{t-1} * r_t)W^H + b^H \tag{3}$$

where     $*$ = denotes the scalar product of two vectors.

Finally, applying the current candidate hidden state $\widetilde{H}_t$ and the previous hidden state $\widetilde{H}_{t-1}$ to implement the following linear combination that satisfies the sum of weighted coefficient be of a value 1.

$$H_t = (1 - z_t) * \widetilde{H}_t + z_t * H_{t-1} \tag{4}$$

where     $H_t$ = is the output of the current hidden state.

#### 2.3.2 Support Vector Machines

The SVM algorithm has performed very well on a wide range of problems and has become one of the most powerful methods in machine learning for both classification and regression (Kampouraki et al., 2009; Sapankevych & Sankar, 2009).

The reason for using SVM in our approach is that this algorithm is less prevalent in the field of meteorology than other machine

learning methods, but it has been successfully used to predict tornadoes (Adrianto et al., 2009; Trafalis et al., 2003) and temperature (Radhika & Shashi, 2009).

Linear SVM was introduced by (VAPNIK, 1963) for binary classification; it separates data into two classes by constructing a hyperplane in the predictor space that best separates the two classes (Jergensen et al., 2020).

During training, the linear SVM learns to maximize the margin or the average Euclidean distance between the hyperplane and the correctly classified samples (Jergensen et al., 2020).

The majority of real-world data are not linearly separable. Consequently, nonlinear kernels (Cortes & Vapnik, 1995; Vapnik, 1995) are frequently used to transform the predictor space implicitly.

In this study, the linear kernel, which is defined in equation 5, was used:

$$K_{linear} = (x_1 w_1 + x_2 w_2 + \cdots + x_M w_M) + c$$

$$= x . w + c \qquad (5)$$

where $x$ and $w$ = are predictor vectors for two examples, both of length M.

$M$ = is the number of predictors.

$c$ = is a hyperparameter, which encourages the model to overfit when too small and underfit when too large.

### 2.4 Methodology Adopted

The methodology used in this study consists of two major parts (Figure 2): The first one aims to predict the different characteristics of storms (wind speed, pressure, humidity, temperature, and wave height), which represents a univariate time-series prediction, and the second part focuses on predicting the occurrence of storms based on their characteristics.
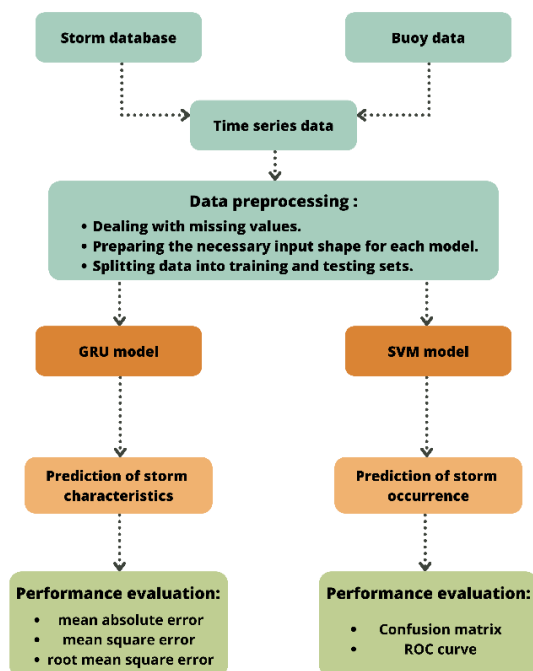


**Figure 2**. Methodology adopted in this study.

To achieve these goals; the following steps were taken: First, data collection: a storm database containing all storm events that have occurred in the study area over the last 25 years was used, in conjunction with buoy data that represents hourly records of wind speed, pressure, humidity, temperature, and wave height. Daily values for each characteristic were calculated from these records and then combined with the storm database to create a final time-series data that represents a day-by-day record of weather and marine data, in addition to the exact days that have known the occurrence of a storm. The final time series data created can be used to predict storm occurrence and characteristics.

Then, data pre-processing, which aims to prepare the data for the implementation of the algorithms. This step involves dealing with missing values and then scaling the features to normalize all independent variables. Next, the data was divided into training and testing sets; 80% of data was used for the training, and the last 20% was used to test the effectiveness of the developed models.

The third step is data processing. Five GRU models were developed to predict storm characteristics (wind speed, pressure, humidity, temperature, and wave height). Each model was specified for the prediction of a particular feature (a univariate time series prediction). Then, an SVM-based classifier was developed and used to predict storm occurrence by identifying and extracting storm-specific patterns.

Finally, performance evaluation is the last step of the study. The GRU models used to predict storm characteristics were evaluated using three evaluation metrics: mean absolute error, mean square error, and root mean square error, and the SVM classifier used to predict storm occurrence was evaluated using the confusion matrix and ROC (receiver operating characteristics) curve.

## 3. EXPERIMENTAL RESULTS

In this study, GRU and SVM were introduced to predict storm occurrence and characteristics. The GRU model has first used for predicting the different characteristics of storms, and then an SVM classifier was used to predict storm occurrence based on their characteristics. The results of the developed GRU and SVM models are presented separately below.

### 3.1 Prediction of Storm Characteristics

Brittany buoy data, which contains historical records of wind speed, pressure, humidity, temperature, and wave height from 1 January 1996 to 31 May 2021, was used to predict storm characteristics. Since the task is a univariate time series prediction, the values for each storm characteristic should be predicted separately. Therefore, a unique model was created for each of them.

Taking wind speed prediction as an example, a GRU model was created based on the univariate dataset of past wind speed, and all other characteristics were predicted in the same manner. Finally, five GRU models were developed, each designed to predict a particular characteristic (wind speed, pressure, humidity, temperature, and wave height).

The data was split into training and testing sets, with a ratio of 80 to 20. 80% was used to train the model and find the best hyperparameters, then the last 20% of data was used to test the robustness of the final model developed. The prediction results for other characteristics (pressure, humidity, temperature, and wave height) will be presented later in this section.

Figure 3 depicts the GRU prediction results. A light blue curve represents the actual wind speed, while a light brown curve represents the predicted wind speed. As can be observed, the GRU model was successful in following the pattern and accurately predicting the general variability of wind speed.

The GRU model doesn't yield the exact values of actual storm wind speeds. However, the results obtained are still promising as the model was able to predict higher wind speed values than the usual values on other days, which can help indicate the occurrence of a storm. For example, the wind speed of storm Zeus, which hit the study area on 6 March 2017, with a value of 19.72 m/s, was predicted by the GRU model to be 13.07 m/s.
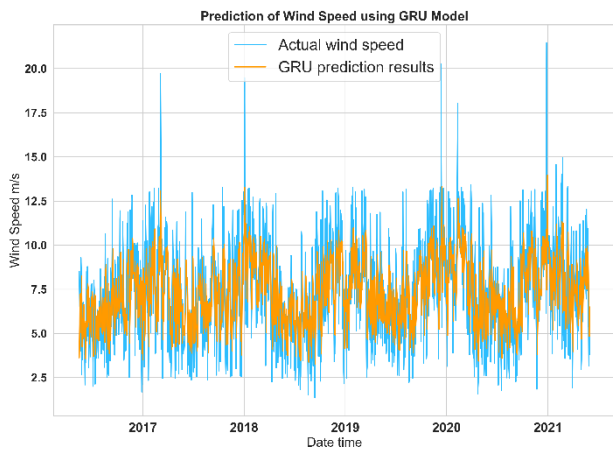


**Figure 3**. Wind speed prediction results from the GRU model.

To test the prediction accuracy of the GRU model, three evaluation metrics were used: Mean Absolute Error (MAE), Mean Square Error (MSE), and Root Mean Square Error (RMSE), which are defined as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|Pm_i - Pp_i| \qquad (6)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Pm_i - Pp_i)^2 \qquad (7)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Pm_i - Pp_i)^2} \qquad (8)$$

where  $n$ = is the number of samples.
$P_{mi}$ = represents the real value.
$P_{pi}$ = is the predicted value.

The evaluation of error metrics shows that the GRU model has few prediction errors. It has generated MAE, MSE, and RMSE values of 1.829, 5.309, and 2.304, respectively.

The prediction results for other storm characteristics (wave height, temperature, pressure, and humidity) are shown in Figure 4. The GRU model has successfully predicted the general variability and all the characteristics of storms, as shown in the figure. Therefore, it appears that the GRU model can be used as an effective tool for the prediction of storm characteristics.
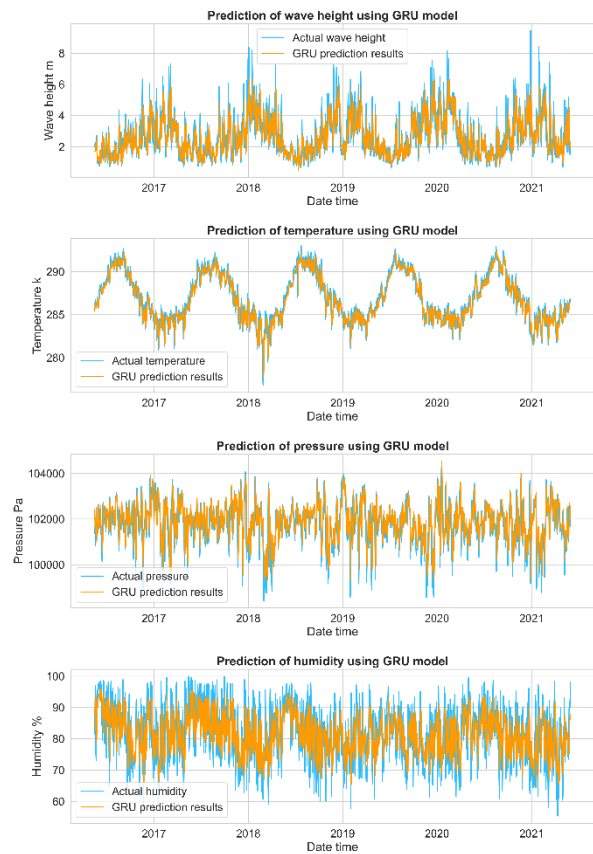


**Figure 4**. Prediction of storm characteristics; wave height, temperature, pressure, and humidity using the GRU model.

## 3.2 Prediction of storms

In this second part, a binary SVM classifier was developed to predict storm occurrence based on their characteristics. To achieve this goal, multivariate time series data was created by combining the storm database and the buoy data to predict storm characteristics. The multivariate time series data represent historical measurements of wind speed, temperature, pressure, humidity, and wave height from 1 January 1996 to 31 May 2021, in addition to the target variable to be predicted, which is in the range of 0 and 1, where 1 represents the occurrence of a storm and 0 indicates that there is no storm. This time series data was divided into training and testing at the ratio of 80 to 20%; 80% for training and 20% for testing the model's performance.

In this study, there were two classes; storms and no storms. The storm class represents the positive class with 68 samples, and the no storm class represents the negative class with 9215 samples. The prediction outcomes for the SVM model are shown in Figure 5. The predicted storms are represented with points in light brown color, while the actual storms are represented with points in light blue color.
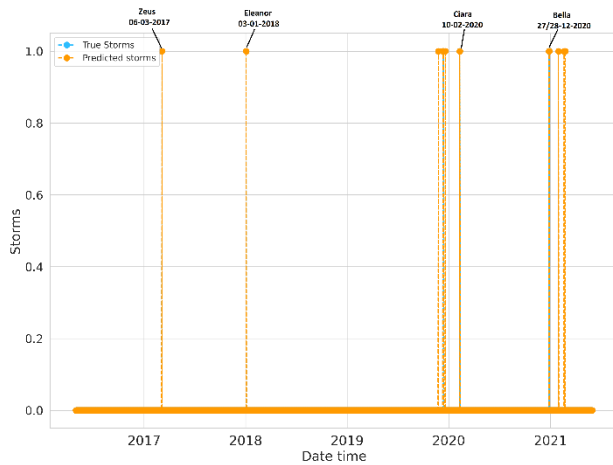
**Figure 5**. Storm prediction results from the SVM model.



**Figure 6**. Confusion matrix of the SVM model.

To assess the performance of the SVM classifier developed, five classification metrics were used: specificity, sensitivity, false-positive rate (FPR), false-negative rate (FNR), and the area under the receiver operating characteristic curve (AUC) metric. These evaluation metrics are not sensitive to changes in data distribution and can be used effectively with imbalanced data, as is the case in this study (Tharwat, 2018).

These assessment metrics can be calculated using the following equations:

$$\text{Specificity} = \text{True negative rate (TNR)} = \frac{TN}{TN+FP} \quad (9)$$

$$\text{Sensitivity} = \text{True positive rate (TPR)} = \frac{TP}{TP+FN} \quad (10)$$

$$\text{FPR (False positive rate)} = \frac{FP}{FP+TN} \quad (11)$$

$$\text{FNR (False negative rate)} = \frac{FN}{FN+TP} \quad (12)$$

where $TP$ = true positives where the model predicted samples correctly as positives. In this case, the storms were classified as storms.
$TN$ = true negatives where the model predicted samples correctly as negatives, no storms predicted as no storms.
$FP$ = false positives where the model mispredicted samples as positives, no storms predicted as storms.
$FN$ = false negatives where the model mispredicted samples as negatives, storms predicted as no storms.

Figure 6 depicts the confusion matrix of the SVM model. As shown, the number of correctly classified samples in the Storm and No-storm classes is 6 and 1844. The TN, TP, FN, and FP values are 1844, 6, 0, and 7, respectively. Consequently, the values of specificity, sensitivity, FPR, and FNR are the following: 0.996, 1, 0.003, and 0.
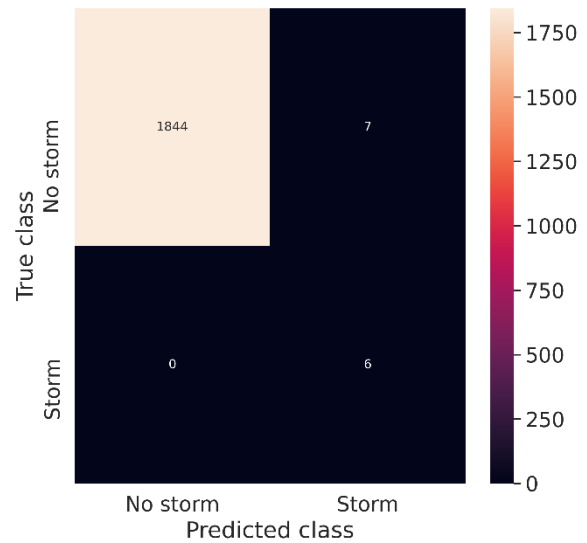
The ROC curve is another evaluation method used in this study to assess the capability of the binary SVM classifier. It is a two-dimensional graph in which the FPR (False positive rate) represents the x-axis and the TPR (True positive rate) represents the y-axis. It can be generated by changing the confidence score threshold (Tharwat, 2018). The AUC value is a metric extracted from the ROC curve and used to evaluate the model's performance. The AUC metric ranges from 0 to 1, and a bigger value indicates a better model. Finally, the SVM binary classifier has proven its efficiency for predicting storm occurrence since it has an AUC value of 1, as shown in Figure 7.
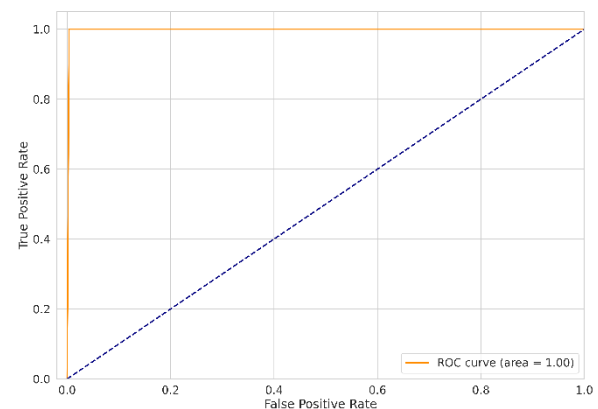


**Figure 7**. ROC curve of the SVM model.

## 4. SUMMARY AND DISCUSSION

Artificial intelligence, specifically machine learning and deep learning methods, has recently exploded in popularity in many fields, including meteorology (McGovern et al., 2019). The remarkable results obtained by these methods have prompted experts to introduce this concept into their various research directions in meteorology. For example, a deep learning approach is currently being used to forecast severe convective weather in China (Zhou et al., 2019).

The high performance of machine learning and deep learning methods in meteorology is also supported by findings from (Lu

et al., 2020), who showed a Mask region-based convolutional neural network (Mask R-CNN) model accurately identified extratropical cyclones with strong winds along the Northern Hemisphere Ocean coasts. (Lu et al., 2020) also found that the number of identified cyclones increased by 8.29% compared to the results obtained by the traditional method. Consequently, we also examine the efficiency of an artificial intelligence approach in the context of storm prediction. Therefore, this study targeted the building of time series prediction models to predict storm occurrence and characteristics, which could be used globally to mitigate the disastrous consequences of these extreme events by taking the necessary precautions.

The paper's main contribution is applying a new artificial intelligence approach using two of the most advanced machine learning and deep learning algorithms, Support Vector Machine (SVM) and Gated Recurrent Unit (GRU) Neural Network.

Experiments were carried out using a database of storm events in the western regions of France over the past 25 years and buoy data representing historical measurements of wave height, wind speed, temperature, pressure, and humidity since 1996.

As a first step, the GRU model was used to predict the different characteristics of storms (wind speed, pressure, humidity, temperature, and wave height). Each storm characteristic was predicted separately, and a GRU model was created for each of them based on past data. (Khosravi et al., 2018) also developed a time-series prediction model using machine learning algorithms to predict wind speed over Brazil based on past measured wind speed data values. The results demonstrated that the adopted method could successfully predict wind speed with high accuracy.

Wind speed prediction is one of the most critical aspects of storm events in recent years. (Yang et al., 2017, 2019) have recently proposed the Bayesian linear regression to predict wind speed for storms that impacted the northeast United States based on a database composed of historical storms. The lower values of root mean square error indicate the models' high performance for storm wind speed prediction.

Our analyses extend these recent studies by considering the prediction of other storm features in addition to wind speed. The method used will result in the prediction of different storms characteristics (wind speed, wave height, temperature, pressure, and humidity) and the exact days of their occurrence, which can help reduce and anticipate the impacts of upcoming events. Several evaluation criteria are applied to evaluate the performance of the developed GRU models in terms of prediction accuracy. Mean absolute error, mean square error, and root mean square error between actual data and predicted ones were used. The developed models were found to make few prediction errors, which proves the efficiency of these models for predicting all storms characteristics.

In the second step of this study, an SVM-based classifier was applied to identify storm-specific patterns and predict storm occurrence. The same hypothesis was applied by (Nayak & Ghosh, 2013) to predict extreme rainfall events using a support vector machine to identify those specific patterns for extreme rainfall events and then apply an SVM-based classifier for extreme rainfall classification and prediction.

The SVM-based classifier developed in this study effectively predicted storm occurrence and achieved high performance in

terms of all the evaluation metrics adopted (specificity, sensitivity, and AUC score).

The findings revealed that the models mentioned above (GRU and SVM) could serve as an effective tool for predicting storm occurrence and characteristics, as both models have performed very well and produced good generalization ability with unseen data. Although future studies will be needed to address the lack of skill in making a long-term prediction of storms characteristics, the GRU model can only generate short-term predictions. Also, the GRU model predicted lower values than the actual values of storms characteristics. Therefore, further investigations into which models other than GRU and SVM can improve the prediction are necessary.

Finally, considering the results obtained, our results appear promising overall. The adopted methodology can predict future storms characteristics and occurrence, which can help avoid the severe damage of these extreme events.

## REFERENCES

Adrianto, I., Trafalis, T. B., & Lakshmanan, V. (2009). Support vector machines for spatiotemporal tornado prediction. *Http://Dx.Doi.Org/10.1080/03081070601068629*, *38*(7), 759–776. https://doi.org/10.1080/03081070601068629

Athimon, E., & Maanan, M. (2018). Vulnerability, resilience and adaptation of societies during major extreme storms during the Little Ice Age. *Climate of the Past*, *14*(10), 1487–1497. https://doi.org/10.5194/CP-14-1487-2018

Bengio, Y., Simard, P., & Frasconi, P. (1994). Learning Long-Term Dependencies with Gradient Descent is Difficult. *IEEE Transactions on Neural Networks*, *5*(2), 157–166. https://doi.org/10.1109/72.279181

Brunkard, J., Namulanda, G., & Ratard, R. (2008). Hurricane Katrina Deaths, Louisiana, 2005. *Disaster Medicine and Public Health Preparedness*, *2*(4), 215–223. https://doi.org/10.1097/DMP.0B013E31818AAF55

Cho, K., Van Merriënboer, B., Gulcehre, C., Bahdanau, D., Bougares, F., Schwenk, H., & Bengio, Y. (2014). Learning phrase representations using RNN encoder-decoder for statistical machine translation. *EMNLP 2014 - 2014 Conference on Empirical Methods in Natural Language Processing, Proceedings of the Conference*. https://doi.org/10.3115/v1/d14-1179

Cortes, C., & Vapnik, V. (1995). Support-Vector Networks. *Machine Learning*, *20*(3). https://doi.org/10.1023/A:1022627411411

Dao, D. Van, Jaafari, A., Bayat, M., Mafi-Gholami, D., Qi, C., Moayedi, H., Phong, T. Van, Ly, H. B., Le, T. T., Trinh, P. T., Luu, C., Quoc, N. K., Thanh, B. N., & Pham, B. T. (2020). A spatially explicit deep learning neural network model for the prediction of landslide susceptibility. *Catena*, *188*. https://doi.org/10.1016/j.catena.2019.104451

Dedieu, F. (2010). Alerts and catastrophes: The case of the 1999 storm in France, a treacherous risk. *Sociologie Du Travail*, *52*(SUPPL. 1), e1–e21. https://doi.org/10.1016/J.SOCTRA.2010.06.001

Ding, M., Zhou, H., Xie, H., Wu, M., Nakanishi, Y., & Yokoyama, R. (2019). A gated recurrent unit neural networks based wind speed error correction model for short-term wind power forecasting. *Neurocomputing*, *365*. https://doi.org/10.1016/j.neucom.2019.07.058

Dorland, C., Tol, R. S. J., & Palutikof, J. P. (1999). Vulnerability of the Netherlands and Northwest Europe to storm damage under climate change: A model approach based on storm damage in the Netherlands. *Climatic Change*, *43*(3). https://doi.org/10.1023/A:1005492126814

E, J., Ye, J., He, L., & Jin, H. (2019). Energy price prediction based on independent component analysis and gated recurrent unit neural network. *Energy*, *189*, 116278. https://doi.org/10.1016/J.ENERGY.2019.116278

Elman, J. L. (1990). Finding Structure in Time. *Cognitive Science*, *14*(2), 179–211. https://doi.org/10.1207/S15516709COG1402_1

Franzke, C. L. E., & Torelló i Sentelles, H. (2020). Risk of extreme high fatalities due to weather and climate hazards and its connection to large-scale climate variability. *Climatic Change 2020 162:2*, *162*(2), 507–525. https://doi.org/10.1007/S10584-020-02825-Z

Genovese, E., & Przyluski, V. (2013). Storm surge disaster risk management: The Xynthia case study in France. *Journal of Risk Research*, *16*(7). https://doi.org/10.1080/13669877.2012.737826

Ghosh, T., & Krishnamurti, T. N. (2018). Improvements in hurricane intensity forecasts from a multimodel superensemble utilizing a generalized neural network technique. *Weather and Forecasting*, *33*(3). https://doi.org/10.1175/WAF-D-17-0006.1

Goerss, J. S. (2000). Tropical cyclone track forecasts using an ensemble of dynamical models. *Monthly Weather Review*, *128*(4). https://doi.org/10.1175/1520-0493(2000)128<1187:TCTFUA>2.0.CO;2

Haarsma, R. (2021). European Windstorm Risk of Post-Tropical Cyclones and the Impact of Climate Change. *Geophysical Research Letters*, *48*(4), e2020GL091483. https://doi.org/10.1029/2020GL091483

Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. *Neural Computation*, *9*(8), 1735–1780. https://doi.org/10.1162/NECO.1997.9.8.1735

Jahn, M. (2015). Economics of extreme weather events: Terminology and regional impact models. *Weather and Climate Extremes*, *10*, 29–39. https://doi.org/10.1016/J.WACE.2015.08.005

Jergensen, G. E., McGovern, A., Lagerquist, R., & Smith, T. (2020). Classifying convective storms using machine learning. *Weather and Forecasting*, *35*(2). https://doi.org/10.1175/WAF-D-19-0170.1

Kamara, S. I. (1986). THE ORIGINS AND TYPES OF RAINFALL IN WEST AFRICA. *Weather*, *41*(2), 48–56. https://doi.org/10.1002/J.1477-8696.1986.TB03787.X

Kampouraki, A., Manis, G., & Nikou, C. (2009). Heartbeat time series classification with support vector machines. *IEEE Transactions on Information Technology in Biomedicine*, *13*(4). https://doi.org/10.1109/TITB.2008.2003323

Kates, R. W. (1980). CLIMATE AND SOCIETY: LESSONS FROM RECENT EVENTS. *Weather*, *35*(1). https://doi.org/10.1002/j.1477-8696.1980.tb03477.x

Khosravi, A., Machado, L., & Nunes, R. O. (2018). Time-series prediction of wind speed using machine learning algorithms: A case study Osorio wind farm, Brazil. *Applied Energy*, *224*. https://doi.org/10.1016/j.apenergy.2018.05.043

Kron, W., Löw, P., & Kundzewicz, Z. W. (2019). Changes in risk of extreme weather events in Europe. *Environmental Science and Policy*, *100*. https://doi.org/10.1016/j.envsci.2019.06.007

Leckebusch, G. C., Ulbrich, U., Fröhlich, L., & Pinto, J. G. (2007). Property loss potentials for European midlatitude storms in a changing climate. *Geophysical Research Letters*, *34*(5). https://doi.org/10.1029/2006GL027663

Lian, J., Dong, P., Zhang, Y., & Pan, J. (2020). A novel deep learning approach for tropical cyclone track prediction based on auto-encoder and gated recurrent unit networks. *Applied Sciences (Switzerland)*, *10*(11). https://doi.org/10.3390/app10113965

Lu, C., Kong, Y., & Guan, Z. (2020). A mask R-CNN model for reidentifying extratropical cyclones based on quasi-supervised thought. *Scientific Reports 2020 10:1*, *10*(1), 1–9. https://doi.org/10.1038/s41598-020-71831-z

McGovern, A., Lagerquist, R., Gagne, D. J., Jergensen, G. E., Elmore, K. L., Homeyer, C. R., & Smith, T. (2019). Making the black box more transparent: Understanding the physical implications of machine learning. *Bulletin of the American Meteorological Society*, *100*(11). https://doi.org/10.1175/BAMS-D-18-0195.1

Meng, F., Song, T., Xu, D., Xie, P., & Li, Y. (2021). Forecasting tropical cyclones wave height using bidirectional gated recurrent unit. *Ocean Engineering*, *234*. https://doi.org/10.1016/j.oceaneng.2021.108795

Mosavi, A., Ozturk, P., & Chau, K. W. (2018). Flood prediction using machine learning models: Literature review. In *Water (Switzerland)* (Vol. 10, Issue 11). https://doi.org/10.3390/w10111536

Nayak, M. A., & Ghosh, S. (2013). Prediction of extreme rainfall event using weather pattern recognition and support vector machine classifier. *Theoretical and Applied Climatology*, *114*(3–4). https://doi.org/10.1007/s00704-013-0867-3

Pouzet, P., & Maanan, M. (2020). Climatological influences on major storm events during the last millennium along the Atlantic coast of France. *Scientific Reports*, *10*(1). https://doi.org/10.1038/s41598-020-69069-w

Pouzet, P., Maanan, M., Sabine, S., Emmanuelle, A., & Robin, M. (2019). Correlating three centuries of historical and geological data for the marine deposit reconstruction of two depositional environments of the French Atlantic coast. *Marine Geology*, *407*. https://doi.org/10.1016/j.margeo.2018.10.014

Radhika, Y., & Shashi, M. (2009). Atmospheric Temperature Prediction using Support Vector Machines. *International Journal of Computer Theory and Engineering.* https://doi.org/10.7763/ijcte.2009.v1.9

Ren, F. M., Trewin, B., Brunet, M., Dushmanta, P., Walter, A., Baddour, O., & Korber, M. (2018). A research progress review on regional extreme events. *Advances in Climate Change Research*, *9*(3), 161–169. https://doi.org/10.1016/J.ACCRE.2018.08.001

Sacré, C. (2002). Extreme wind speed in France: the '99 storms and their consequences. *Journal of Wind Engineering and Industrial Aerodynamics*, *90*(10), 1163–1171. https://doi.org/10.1016/S0167-6105(02)00229-5

Sapankevych, N., & Sankar, R. (2009). Time series prediction using support vector machines: A survey. *IEEE Computational Intelligence Magazine*, *4*(2). https://doi.org/10.1109/MCI.2009.932254

Stephenson, D. B. (2008). Definition, diagnosis, and origin of extreme weather and climate events. In *Climate Extremes and Society* (Vol. 9780521870283). https://doi.org/10.1017/CBO9780511535840.003

Sun, W., Bocchini, P., & Davison, B. D. (2020). Applications of artificial intelligence for disaster management. *Natural Hazards 2020 103:3*, *103*(3), 2631–2689. https://doi.org/10.1007/S11069-020-04124-3

Tharwat, A. (2018). Classification assessment methods. *Applied Computing and Informatics*, *17*(1). https://doi.org/10.1016/j.aci.2018.08.003

Trafalis, T. B., Ince, H., & Richman, M. B. (2003). Tornado detection with support vector machines. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *2660*. https://doi.org/10.1007/3-540-44864-0_30

Trafalis, T. B., Santosa, B., & Richman, M. B. (2004). Rule-based support vector machine classifiers applied to tornado prediction. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *3038*. https://doi.org/10.1007/978-3-540-24688-6_88

Usbeck, T., Wohlgemuth, T., Dobbertin, M., Pfister, C., Bürgi, A., & Rebetez, M. (2010). Increasing storm damage to forests in Switzerland from 1858 to 2007. *Agricultural and Forest Meteorology*, *150*(1). https://doi.org/10.1016/j.agrformet.2009.08.010

VAPNIK, V. (1963). Pattern recognition using generalized portrait method. *Automation and Remote Control*, *24*.

Vapnik, V. N. (1995). The Nature of Statistical Learning Theory. In *The Nature of Statistical Learning Theory*. https://doi.org/10.1007/978-1-4757-2440-0

Yang, J., Astitha, M., Anagnostou, E. N., & Hartman, B. M. (2017). Using a Bayesian regression approach on dual-model windstorm simulations to improve wind speed prediction. *Journal of Applied Meteorology and Climatology*, *56*(4). https://doi.org/10.1175/JAMC-D-16-0206.1

Yang, J., Astitha, M., & Schwartz, C. S. (2019). Assessment of Storm Wind Speed Prediction Using Gridded Bayesian Regression Applied to Historical Events With NCAR's Real-Time Ensemble Forecast System. *Journal of Geophysical Research: Atmospheres*, *124*(16). https://doi.org/10.1029/2018JD029590

Zhang, W., Han, L., Sun, J., Guo, H., & Dai, J. (2019). Application of Multi-channel 3D-cube Successive Convolution Network for Convective Storm Nowcasting. *Proceedings - 2019 IEEE International Conference on Big Data, Big Data 2019*. https://doi.org/10.1109/BigData47090.2019.9005568

Zhou, K., Zheng, Y., Li, B., Dong, W., & Zhang, X. (2019). Forecasting Different Types of Convective Weather: A Deep Learning Approach. *Journal of Meteorological Research*, *33*(5). https://doi.org/10.1007/s13351-019-8162-6