Prediction Of Icing Risk Degree On Aircraft With Machine Learning Algorithms

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Research Article

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Abstract

Icing poses a threat for aircrafts, as it does for all other areas in general. From the past to present, many aviation accidents have occurred and are still occurring due to icing. Scientists have proposed several solutions to eliminate or minimize the problem of icing. To eliminate icing, de-icing systems have been introduced and anti-icing systems have been put into practice to prevent icing and these methods are presently being developed. However, these systems are generally put into use in aircrafts under pilot control. The pilot operates anti-icing and de-icing systems when she or he senses the presence of ice. The pilot's carelessness or lack of training then plays a major role in the occurrence of accidents. The study has tested seven different artificial intelligence algorithms for an aircraft that could lead to a direct operation of the de-icing/anti-icing system as a result of the estimated risk of ice. Simulink and Waijung blockset-supported modelling have been conducted and the diagram that will estimate the icing risk rating for different input values was embedded in the STM32F4 Discovery controller board and the results of the icing prediction were observed using RGB led. 88.59 percent value is obtained by the boosting algorithm for the optimum icing risk rating prediction. In conclusion, a model is proposed to ensure automatic activation of the anti-icing and de-icing systems in aircraft that will be used for predicting icing.

1 Introduction

Since prehistorical times, humans have invented for reasons such as facilitating their daily lives and ensuring their safety. However, inventions in history brought along some problems. The biggest problem that arose from the invention of aircraft were the fatal accidents caused by aircraft. Focusing on taking precautions by learning from bad experiences, human beings also try to eliminate or minimize fatal accidents caused by aircraft. One of the most important types of accidents that require precautions, which is the subject of fatal accidents in aviation almost every year, is icing. According to the Air Safety Institute, 388 accidents, which represent 12 percent of all aircraft accidents during 1990-2000, occurred due to ice. [1]. This figure shows the significance of ice-related accidents and indicates that it is something that should be paid attention to. Precautions have also been taken against ice-related accidents and are still being taken. Anti-Icing systems have been recommended to prevent ice formation, and de-icing systems have been recommended to eliminate current icing. These mechanistic, chemical, electrical, and energy rules are being used and developed today [2]. These systems are generally available in aircraft, but are usually left to pilot use. Pilots operate the anti-icing and de-icing systems when he or she detects the presence of icing. This can lead to accidents caused by the pilot [3].

Aircraft icing has been the study of scientists from many fields. Palacios et. al. have introduced a non-thermal ultrasonic-based anti-icing system for rotor blades. They have studied the effects of ultrasonic waves on icing strength at different frequencies and amplitudes [4]. Aykan et. al. have tried to detect and control the icing on wings of the F16 fighter jet during a flight. They identified the aircraft's icing model with the parameters known as stability variants and determined the icing after monitoring the changes in the Extended Kalman filter (EKF) innovation process of the aircraft's dynamic characteristics [5].

Boduroğlu studied on a thermal anti-icing system applicable to the wings of a Boeing 737-800 aircraft. Thermal anti-icing systems operate by blowing hot air on wings which are exposed to icing. In the study, the heat required against icing was calculated using boundary layer equations, thereby obtaining the hot air blowing capacity [6]. Fenar tried to predict the icing risk in his study using artificial neural networks. Initially, artificial neural networks were trained with ambient temperature, amount of water in the air, and freezing point, then the icing risk was estimated accordingly [3]. Johansen and Sorensen recommended an electro thermal-based autonomous icing protection system for drones. They have an electrothermal welding on the surface of the aircraft, a central control unit as well as an icing protection solution. The control unit is equipped with a built-in bundle of atmospheric sensors measuring ambient atmospheric conditions. When an icing risk arises, control algorithms check the energy supplied to electro-thermal sources for heat control [7]. Gliwa et. al. provided automatic control of anti-icing system for Diamod DA42 aircraft. They created their work by using Matlab's Fuzzy Logic Toolbox package. They took four parameters into consideration; weather temperature, cloud water content, temperature of the plane and rain. In the first stage, they determined the potential ice density in the aircraft and then automatically adjusted the anti-icing system [8]. In its study, Akbal used numerical calculations on the aircraft wing to calculate the ice thickness and determine the type of ice in the area where the maximum air velocity was seen. He calculated the time after which the accumulation of ice on the wings switched to the glassy ice and the thickness of the water layer on the surface during the transition to the glassy ice [9]. Akbal also developed a computer program using Fortran, Techplot, and GetGraph Digitizer software for glaciation simulation on wings, tail, and cylinder geometries to solve the icing problem. [10]. Vertuccio et. al. designed thermal anti-icing system to prevent icing on aircraft surfaces using flexible graphene film/paper. They used less power than other solutions to break the ice with the flexible heating paper they designed [11] while offering high mechanical properties. Li et. al, estimates maximum ice thickness, icing area, and icing risk rating using XGBoost supervised learning algorithm. In XGBoost model, the liquid water content, droplet diameter and exposure time were set as input parameters. They used precision, recall, F-score and confusion matrix in their icing risk rating estimation. Out of 521 data, 512 data was classified correctly, whereas 9 data was classified incorrectly. The accuracy, precision and F-score values were above 0.95 [12]. Shen et. al. combined the mass and temperature transfer model of anti-icing surface with the shell temperature equations to simulate aircraft thermal anti-icing systems and to decode the combined heat transfer of air droplet flow and solid surface. The method, which has been developed based on the heat flow, can directly decode the thermodynamic model of the back-flow water, while temperature-based methods have been shown to have reached the solution at a higher calculation rate[13]. In this study, icing risk level was estimated based on meteorological parameters. Temperature, humidity, aircraft temperature, rain parameters as input parameters have estimated the risk of icing. Seven different artificial intelligence applications were used in the risk of icing prediction, namely the nearest neighbour algorithm, artificial neural networks (ANN), support vector machines (SVM), and random forest, bagging, boosting from ensemble trees and decision trees. Ten-fold cross-validation was applied to the artificial intelligence methods. In order to determine the optimum method for classification, four different evaluation metrics were used to determine the evaluation process: accuracy, precision, recall and F score. The optimum classification method among the applied artificial intelligence methods was validated using different evaluation metrics. Classification method that yield the most accurate results from the applied artificial intelligence algorithms is modeled so that it can be used with simulink and embedded in the STM32F4 discovery control board using waijung blocks.

2 Problem Description

2.1 Icing on Aircrafts

Icing in aircraft is a major risk related to flight safety caused by atmospheric conditions that depend on meteorological conditions. Ice in aircraft can occur while the aircraft is on the land or in the air [14]. Icing density in aircraft is divided into different categories. The objective is to define and report on the icing. To determine the severity of the icing, the US Federal Aviation Company has identified four main categories, namely trace, light, moderate and severe. These categories and their descriptions are given in Table 1 [14, 15].

Table 1
Identification of icing risk levels [15]

Category	Description
Trace	This is the degree of icing that is noticeable, although difficult to see. Appears as a white line. De-icing and anti-icing equipment is not required unless the icing condition lasts more than one hour.
Light	If aircraft icing continues for more than 1 (one) hour, the white-line ice forming at the front edge of the wings starts to expand and the aircraft's performance is affected. Therefore, the icing protection system needs to be operated.
Moderate	Even a short-term icing period is very dangerous. With the anti-icing system or icing-protection system, the icing must be prevented or removed from the aircraft. It may be necessary to stop ice, change altitude and change direction in the moderate-level icing.
Severe	At this stage, the aircraft should return to safe airspace conditions as soon as possible. The aircraft needs to change altitude or direction. Because even if the ice-protection or anti-icing equipment is activated, the icing is unstoppable, and the effect of the icing is not diminished.

If the pilot is late to operate the de-icing and anti-icing system, as illustrated by Table 1, the aircraft may be losing control and causing an accident. If the icing occurs when the aircraft is on the ground and the aircraft takes off, a possible accident may be inevitable. On December 27, 1991, icing on the wings of Flight 751 for Scandinavian Airlines have not been detected, and shortly after taking off the plane crashed [9], which can be regarded as a concrete example. To avoid the pilot-induced errors, Systems are being developed to determine whether or not there is icing in the aircraft and detect its degree.

2.1 Artificial Intelligence

Artificial intelligence has arisen through an effort to put uniquely human qualities into machines that support computers or computers. In artificial intelligence, the goal is to artificially transfer the behavior of assets to machines. Machine learning is a subset of artificial intelligence. Machine learning is the application for parsing, learning, and forecasting data using algorithms [16]. In the literature, machine learning strategies are studied under three key topics: supervised learning, unsupervised learning and reinforcement learning. In the supervised learning model, the model is trained by providing input data and output data. On the other hand, in unsupervised learning, the output data is not given to the network, thus learning is possible according to the relationship between entries. Reinforcement learning uses a benchmark that evaluates and compares the obtained output with the input. [17] The study uses artificial neural networks (ANN) algorithms, k-nearest neighbor algorithm (KNN), support vector machines (SVM), decision trees, bagging algorithms, boosting algorithms, and random forest algorithms.

2.3 Performance Evaluation Metrics

Performance evaluation metrics are used in evaluating trained models. Performance evaluation metrics allow models to be compared to their evaluation result. Generally, it is achieved by using the error matrix that is created for binary classification. Error matrix given on Table 2 [18]. Performance evaluation metrics are used in evaluating trained models. Performance evaluation metrics allow models to be compared to their evaluation result. Generally, it is achieved by using the error matrix that is created for binary classification. Error matrix given on Table 2 [18]. In Table 2, True Positive (TP) represents data that is correctly tagged for the positive class. True Negative (TN) represents the correctly tagged data for the negative class. False Positive (FP) represents mistagged data from the negative class, and False Negative (FN) represents data that is mistagged from the positive class.

The evaluation metrics used to evaluate the classification performance are set forth on Table 3. [18]

Table 2
Error matrix consisting of binary class [18]

		Prediction Class	
		Positive	**Negative**
Actual Class	Positive	True Positive (TP)	False Negative (FN)
	Negative	False Positive (FP)	True Negative (TN)

Evaluation metrics used to evaluate classification performance are given in Table 3. [18].

Table 3 Performance evaluate metrics

Performance Evaluation Metric	Formula	Definition
Accuracy	$\frac{TP + TN}{TP + FP + TN + FN}$	It is the ratio of correctly classified data belonging to positive and negative classes to all data.
Recall	$\frac{TP}{TP + FN}$	It is the ratio of correctly classified data belonging to the positive class to all the data belonging to the positive class.
Precision	$\frac{TP}{TP + FP}$	It is the ratio of correctly classified data belonging to the positive class to all positively labeled data.
F-Score	$\frac{2 * \text{Recall} * \text{Precision}}{\text{Recall} + \text{Precision}}$	The sensitivity and precision of performance evaluation criteria is the harmonic mean.

2.4 Dataset

The degree of icing data set was based on the works in literature and the experimental data used by Gliwa et et al. for aerospace students from the Polish Air Force. The data set consists of four inputs and four outputs. Temperature and humidity are the most important parameters that affect icing. The degree of icing has been estimated by taking into account temperature, humidity, aircraft temperature and precipitation. The data set contains 3,025 pieces of data. For the four input values, the output is created as "no icing (0)", "trace(1)", "moderate(2)" and "severe (3)". Therefore, icing risk rating is estimated based on four classes [8].

2.5 Waijung Blokset

The Waijung block set is a toolbox working under Simulink developed by Taiwanese company Aimagin. It is possible to develop Simulink based applications using Waijung block sets. The block set can be downloaded directly from the web page "Waijung Bockset" [19]. It is preferred for programming because of the simplicity of the block set and its application development capacity[20].

3 Simulation Results

3.1 Application Results of AI Methods

Ten-fold cross-validation is used in the artificial intelligence models applied in the study, which is often preferred in the literature. This section provides results of artificial intelligence algorithms applied to the data set.

3.1.1 AAN Application Results

When artificial neural networks are used to classify a data set, optimum classification accuracy was obtained when the number of layers was one and neuron number was twenty-five. The values for the model's confusion matrix are given in Table 4. When Table 4 was examined, a total of 1923 data were classified correctly, while 1102 data were classified incorrectly.

Table 4
Artificial neural networks confusion matrix

Confisuon Matrix				
Actual Predict	**No Icing**	**Light**	**Moderate**	**Severe**
No Icing	662	157	102	3
Light	183	402	141	10
Moderate	77	86	360	149
Severe	5	17	172	499

3.1.2 KNN Application Results

For KNN algorithm, an artificial intelligence method used to classify data set, a model was trained for different k neighboring values, and the optimum classification accuracy was obtained by selecting a k value of 14. Euclid distance was used for the distance calculations of K neighbors. Fig. 1 shows the accuracy given by the model with different k values.

Selecting K value 14 trained the model and the confusion matrix is given in Table 5. When Table 5 is examined, a total of 1,754 data are classified correctly and 1,271 data is classified incorrectly.

Table 5
KNN confusion matrix

Confusion Matrix				
Actual Predict	**No Icing**	**Light**	**Moderate**	**Severe**
No Icing	532	207	167	18
Light	170	344	164	58
Moderate	71	90	416	95
Severe	21	35	173	464

3.1.3 SVM Application Results

Support vector machines have been trained on data sets using different core functions, and optimum classification accuracy is achieved when using radial basis kernel function. Figure 2 shows the change in accuracy of the model based on the kernel functions.

The accuracy model obtained when using radial basis kernel function is given in Table 6. When Table 6 was examined, the model classified 1,705 data correctly and 1,320 data incorrectly.

Table 6
SVM confusion matrix

Confusion Matrix				
Actual Predict	**No Icing**	**Light**	**Moderate**	**Severe**
No Icing	570	176	162	16
Light	209	303	183	41
Moderate	66	97	397	112
Severe	27	23	208	435

3.1.4 Decision Tree Application Results

The accuracy matrix of the decision tree algorithm applied to the data set is given in Table 7. The algorithm 2315 classified data correctly, but 710 data incorrectly.

Table 7
Decision trees confusion matrix

Confusion Matrix				
Actual Predict	**No Icing**	**Light**	**Moderate**	**Severe**
No Icing	774	141	6	3
Light	131	494	106	5
Moderate	33	59	507	73
Severe	8	5	140	540

3.1.5 Random Forest Algorithm Application Results

The random forest algorithm was applied by changing the number of decision trees it contains. Optimum classification accuracy was obtained when the number of decision trees was 19. Figure 3 shows a visual of the model's accuracy change in the number of different decision trees.

The confusion matrix of the trained model is given when 19 decision trees are selected in Chart 8. Accordingly, a total of 2,674 data were classified as correct and 351 data were classified as incorrect.

Table 8
Random forest confusion matrix

Confusion Matrix				
Actual Predict	**No Icing**	**Light**	**Moderate**	**Severe**
No Icing	853	60	10	1
Light	87	619	26	4
Moderate	23	49	568	32
Severe	2	7	50	634

3.1.6 Bagging and Boosting Algorithm Application Results

The confusion matrix for the bagging algorithm applied to the data set is given in Table 9, and the confusion matrix for the boosting algorithm is given in Table 10.

Table 9
Bagging algorithm application results

Confusion Matrix				
Actual Predict	**No Icing**	**Light**	**Moderate**	**Severe**
No Icing	835	84	4	1
Light	178	483	70	5
Moderate	37	47	519	69
Severe	7	6	92	588

Table 10
Boosting algorithm application results

Confusion Matrix				
Actual Predict	**No Icing**	**Light**	**Moderate**	**Severe**
No Icing	847	66	9	2
Light	72	629	30	5
Moderate	27	50	567	28
Severe	3	8	45	637

3.2 Determination of the Optimum Classification Method

Seven different artificial intelligence algorithms have been applied to the data set. Algorithms are evaluated with performance evaluation metrics, and results are given in Table11.

Table 11
Evaluation of classification methods with performance evaluation metrics

Artificial Intelligence Algorithm Performance Evaluation Metric	**ANN**	**KNN**	**SVM**	**Decision Tree**	**Random Forest**	**Bagging**	**Boosting**
Recall	0.6352	0.5904	0.5744	0.7656	0.8849	0.8034	**0.8867**
Precision	0.6296	0.5829	0.5618	0.7606	0.8811	0.7952	**0.8836**
Accuracy	0.6357	0.5805	0.5636	0.7653	0.8840	0.8017	**0.8859**
F score	0.6324	0.5867	0.5680	0.7631	0.8830	0.7993	**0.8851**

The best way to classify the data set is to be called the boosting algorithm from ensemble methods by Table 11. The sensitivity for the boosting algorithm from ensemble models was found at 88.67%, while precision is 88.36%, accuracy is 88.59%, and F score is 88.51%.

3.3 Analyzing Optimum Classification Method in Simulink

For the optimum AI algorithm embedded in the simulation, the input values are randomly determined by using Repeating Sequence Stair. In Simulink diagram shown in figure 4, sample time was selected at 0.1.

The random temperature values for input repeatedly during the simulation period have been set to [3 -2 1 0 -20 -15 4 2 1 -1 -3 -15 20 30 -57 -45 25 27 20]. Besides, random humidity values are [-1 4 0.1 0.5 -0.1 3

0.8 1 -0.7 0 0.1 0.4 0.7 -0.1 -0.2 4 2 -0.3 2 3]. Random precipitation values are [3 -1 1 0 -0.2 -0.3 -0.4 2 1 1 3 -0.5 -0.2 -0.3 1 0 0.1 2 3 1 0 3 2] and random aircraft temperature values are [54 -20 10 2 -5 -15 4 2 -11 1 -3 40 -15 20 30 -25 -20 -27 55]. Simulation time is 10 seconds.

The codes written in the MATLAB workspace were summoned from Simulink using a function block and embedded in the STM32F4 board with the help of the waijung blokset. The codes written in the MATLAB workspace were summoned from Simulink using a function block and embedded in the STM32F4 board with the help of the waijung blokset.

With an RGB led, it is possible to see the icing risk ratings generated by signals applied to random input as 0 (no icing) with no light, icing risk rating 1 (light) with blue light, icing risk 2 (moderate) with green light and icing risk 3 (severe) with red light. It can be seen in Figure 5, Figure 6 shows icing risk ratings graphs in the output, depending on the input parameters.

4 Conclusion

Icing is one of the major causes of accidents in aviation today. This study attempted to determine icing risk rating by leading from data such as temperature, humidity, precipitation, and aircraft temperature which are taken from a sample aircraft. The study can be briefly summarized as follows: the data set is determined from studies in the literature. AAN, KNN algorithm, decision-tree algorithm, SVM and random forest, bagging and boosting algorithms from ensemble learning algorithms were created. The generated data set is trained with models, and the highest model is identified using performance evaluation metrics. Classification at the highest performance was done by boosting algorithm from ensemble learning algorithm. The sensitivity of the boosting algorithm was 88.67 percent, while precision was 88.36 percent, accuracy was 88.59 percent, and F score was 88.51 percent. The trained parameters of the increment algorithm were saved and called to be used for prediction purposes in new input data that can be entered from Simulink via the function block in Simulink. The trained parameters of the increment algorithm were saved and called to be used for forecast purposes in new input data that can be entered from Simulink via the function block in Simulink.

Random entries from Simulink have been shown, and icing risk rating prediction algorithm that has the best performance for classification has been shown as boosting algorithm and results were shown in graphs. The simulated model in Simulink is embedded in the STM32F4 discovery board by the blocks in the waijung blockset library. Icing prediction is observed with RGB LED connected to control board output. At the end of the study, the system that predicts the risk of icing, which can be applied as a solution to the problem, was designed, simulated and embedded in the control board. Anti-icing and ice protection systems can be operated by predicting the icing risk rating, thereby preventing icing accidents caused by the pilots.

Declarations

Authors' Contributions

The study was produced from the master thesis made by Fatmanur ATEŞ under the supervision of Ramazan ŞENOL.

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Ethics declarations

There is no need for any ethical permission in the study.

Conflict of interest

The authors declare that we have no conflict of interest.

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Figures

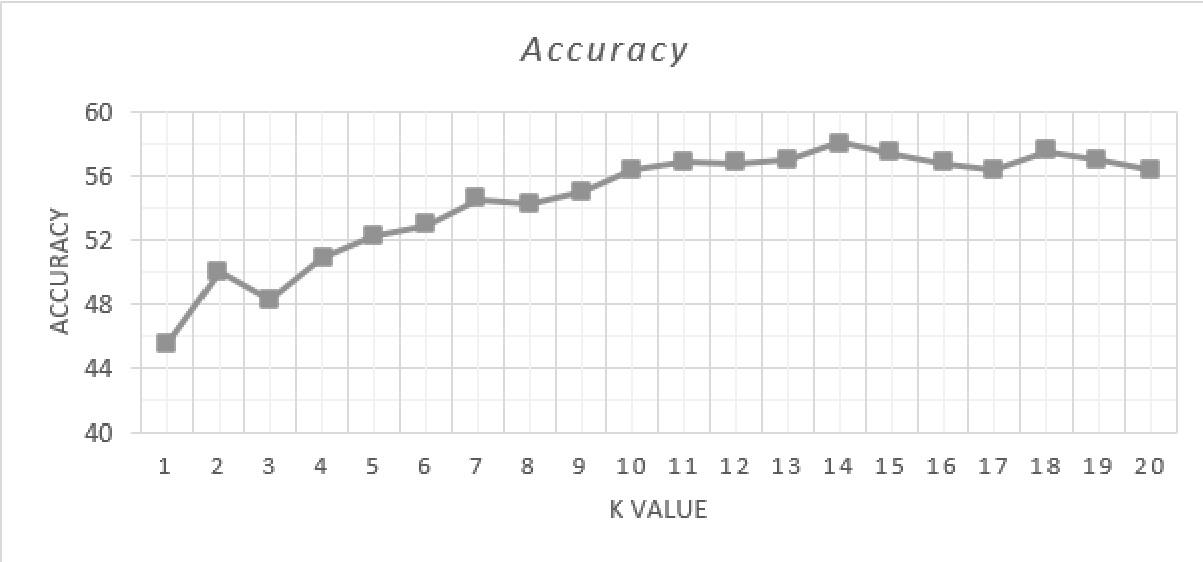

Figure 1

Accuracy results for different k values

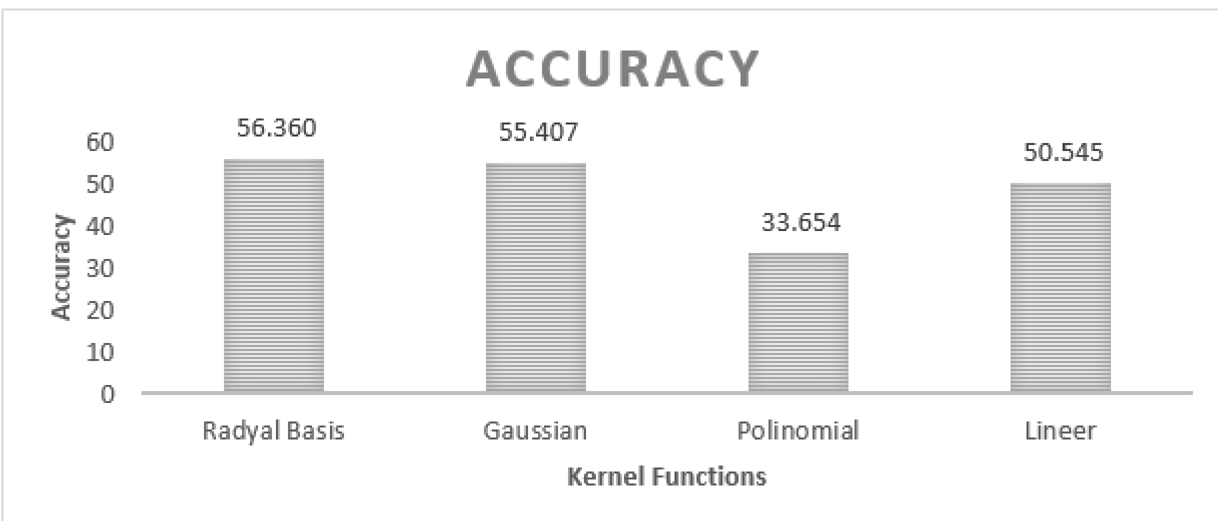

Figure 2

The accuracy of the model using different kernel functions

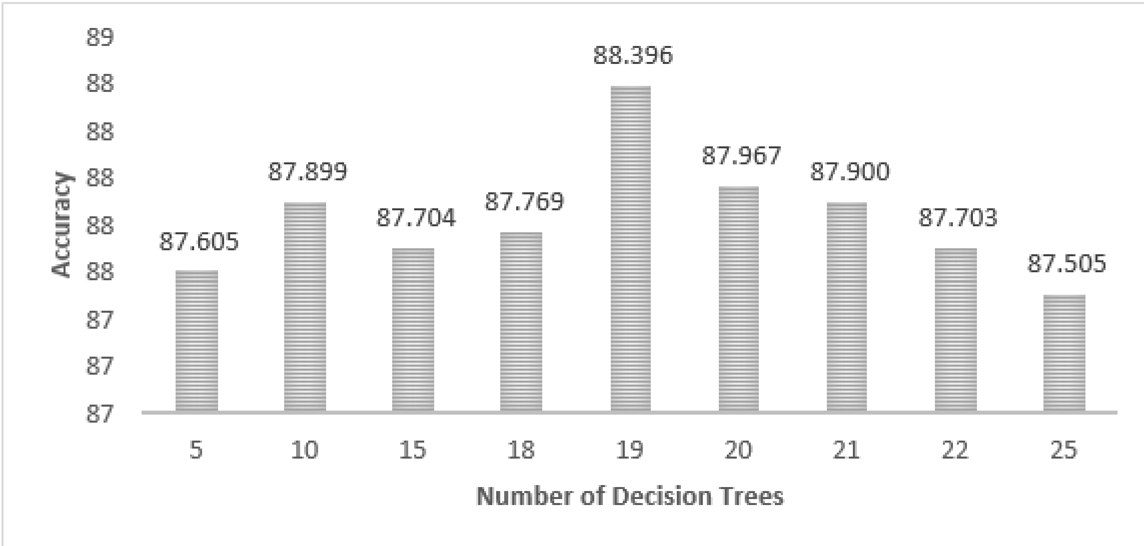

Figure 3

Accuracy change of the model at different number of decision trees

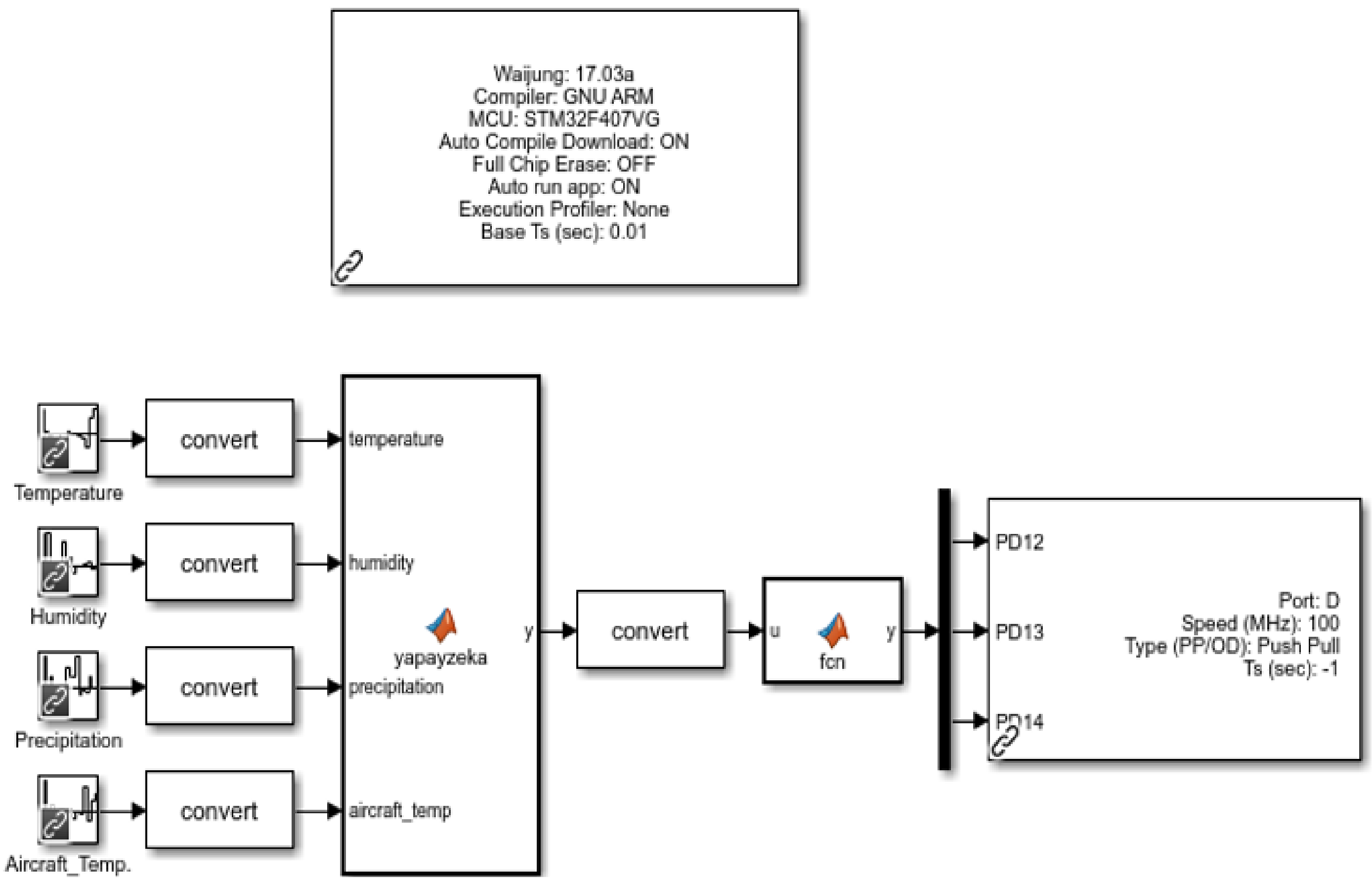

Figure 4

Embedding the optimum classification method into the STM32F board

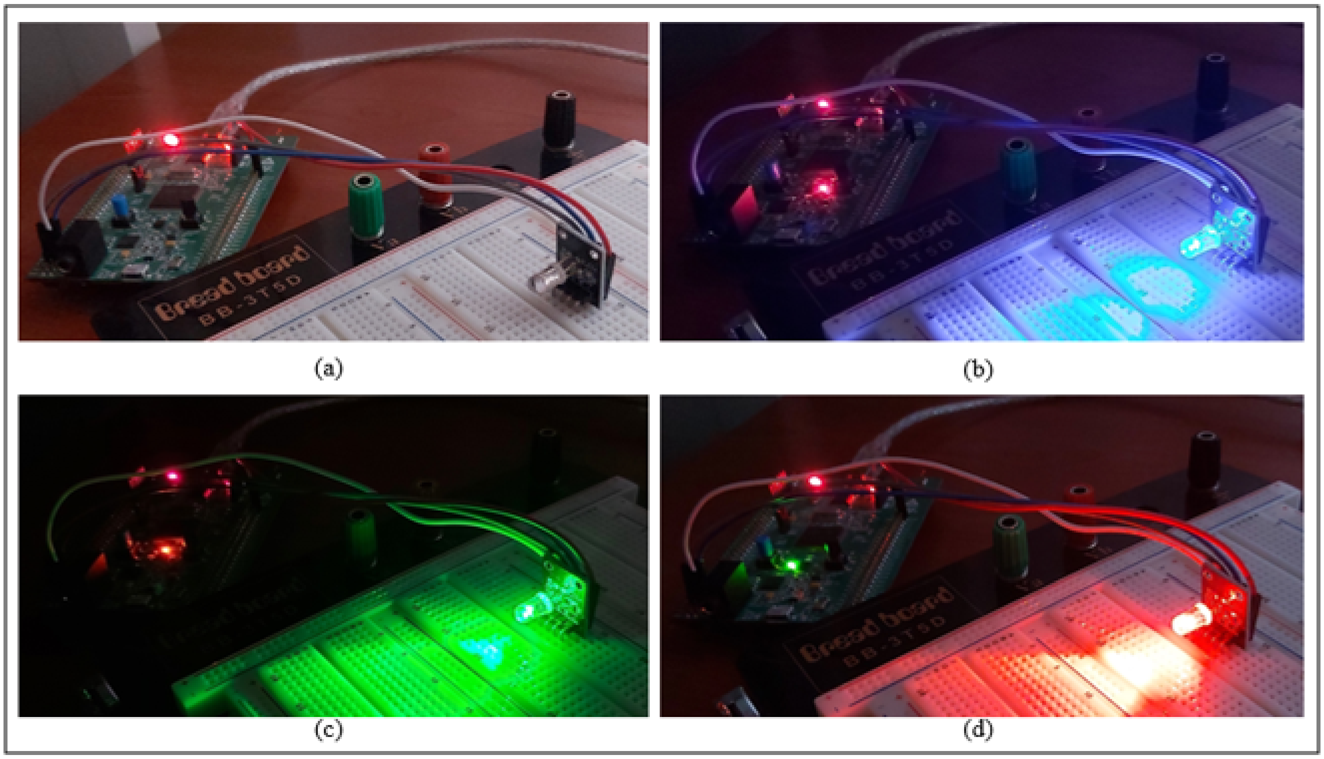

Figure 5

Icing risk levels observed with the help of RGB LED (a) Trace (b) Light (c) Moderate (d) Severe

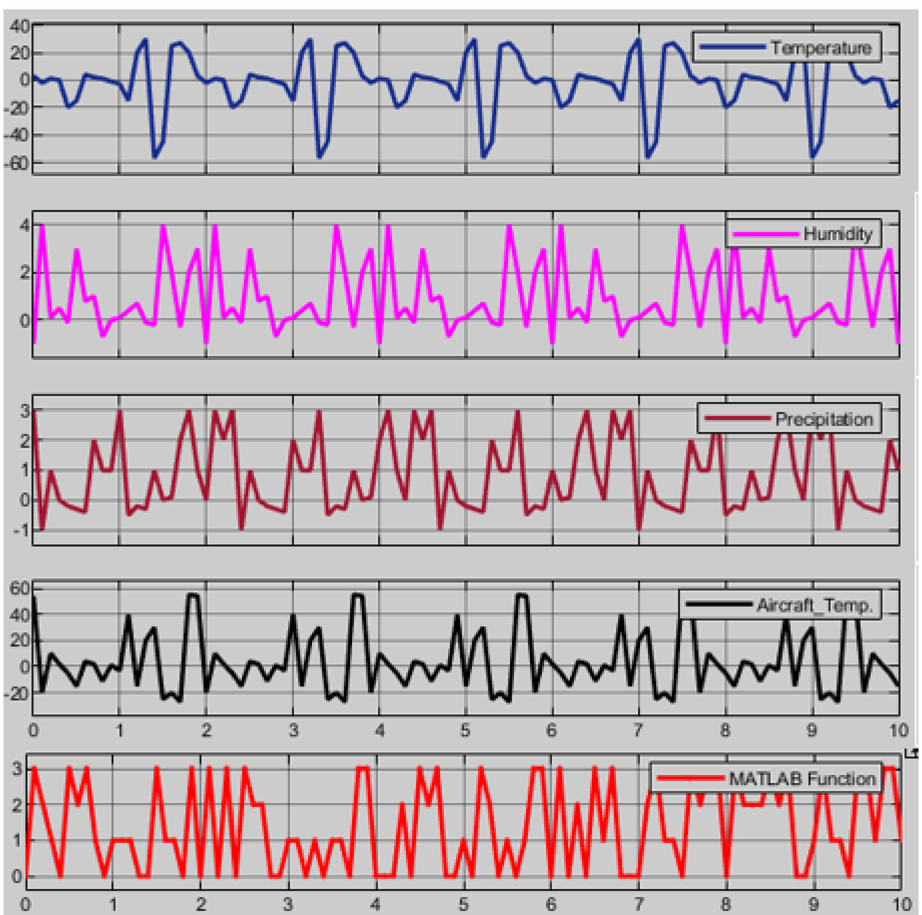

Figure 6

Input and output graphs by random inputs