Machine learning approach for turbulence forecasting using support vector machine

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Abstract. The turbulence can be expressed as small-scale, short term and frequent change to the velocity of air. The turbulence forecasting in the atmospheric boundary layer is very influenced by gradient Richardson number values. In this case, we use the data set were retrieved from Indonesia Meteorology, Climatology and Geophysics in synoptic hour 0000H. In particular, our methods will use Richardson number value and machine learning approaches by using a support vector machine to forecast the Richardson number value and identification the stability of the layer based on the turbulence forecasting. The results will be practically beneficial as utilities can use the predicted values to generate an adequate amount of Richardson number value to avoid grid outages as well as construct dynamic pricing schemes based upon future turbulence.

1. Introduction

The turbulent flows affected by buoyancy lie at the basis not only of many applications on engineering but also within in the atmospheric science. The physical model of the atmosphere is the main component of every forecasting system. Turbulence at the surface is ambitious by solar radiation, the turbulence in turn trigger moist convection[1], [2]. In this case, we focused on identification turbulence on the phenomenon in the lower level of the atmosphere based on the Richardson number. The Richardson number (Ri) describes the atmosphere's ability to sustain turbulence produced through other means by quantifying the ratio of static stability to vertical wind shear[3], [4]. The Richardson number does not specify turbulence intensity; it merely indicates if turbulence can be sustained[5].

Forecast of moderate turbulence is typically issued based upon the presence of areas. In addition, we use a machine learning approach by Support Vector Machine to identification and analysis the turbulence in a low layer in 300 m. The main goal for this paper to predicting the turbulence in the atmospheric boundary layer based on Support Vector Machine (SVM).

2. Data and Method

2.1 Data

The data utilized for this research were retrieved from Badan Meteorologi, Klimatologi dan Geofisika (BMKG) Kualanamu Flight Office. The data for the period January to March 2018 in time observation 00 Hour. The dataset was employed from Sumatera area, with research area in 33544.27 N – 985143.6 E as shown in Fig 1. Meteorological variables such as wind speed, air temperature, and relative humidity were acquired at a pressure level of 300 m.

Figure 1. Research area and collected dataset

2.2 Method

The Richardson number (Ri) and machine learning approach based on SVM are widely used and are acceptable due to their simplicity and applicability. According to [6]–[8], the meteorologist uses the conventional of Richardson number analysis while the latter utilizes gradient temperature at two levels for stability analysis. This research uses the gradient Ri to evaluate the degree of stability condition across in one layer (300 m). The other methods in this paper using a machine learning approach[9]–[15]. In this case, we use SVM to predict the turbulence from Richardson number in the low layer when the climbing flight area. The SVM will solve the following optimization problems [10], [13], [16], [17].

The criteria of turbulence and stability in an atmosphere based on Richardson number can be shown in table 1[8], [18].

As note by [1], [18], the Richardson number between 0 and Richardson critical value 0.25, turbulent flow is generated mostly by forced convection. Negative Ri value estimated is unstable condition due to free convection.

Table 1. The Turbulence Criteria and Stability

Ri Number	Turbulence	Stable/Not Stable
$Ri < 0$	Yes, Strong Convective	thermal not stable
$0.0 < Ri < 0.25$	Yes, Weak Convective	
$Ri > 0.25$	No	

3. Result and Discussions

Based on the result we have strong sign that machine learning-based support vector machine has the ability to achieve high accuracy rates for the turbulence forecasting problem, and consequently believe it would be satisfying to explore this area further.

Table 2. The average monthly of Gradient Richardson Number Value (Ri) for period January to March 2018.

Month	Richardson Number (Ri)
January	4.855179599
February	0.771949482
March	2.398945647

In Table 1, shown the estimate average monthly of Gradient Ri value from three months in low layer boundary, 300 m or 10 feet on Sumatera Area. From the gradient Ri value, period January to March indicates the times of insignificant turbulence with the low layer. The dominant atmospheric condition was stable from January to March 2018.

The turbulence forecasting based on a machine learning approach in SVR can be shown in Fig 2. The volume of Richardson number shown in the blue line. Based on the [18], we indicate there is no turbulence growth for a week to week for each month if we compare to Richardson number which greater than 0.25. and the layer 300 m show in Fig.2 with greater attitude expanse than the other layer has revealed a strongly unstable condition across the specified hour. The orange line is the turbulence forecast. By Support Vector Machine from the orange line, show the result in that a side of the processing steps, there is information regarding the monthly was used to archive high accuracy rates on learning task when the Richardson number is not too large. The initial analysis showed the Turbulence Forecasting by Richardson number value series contained a significant monthly seasonality component.

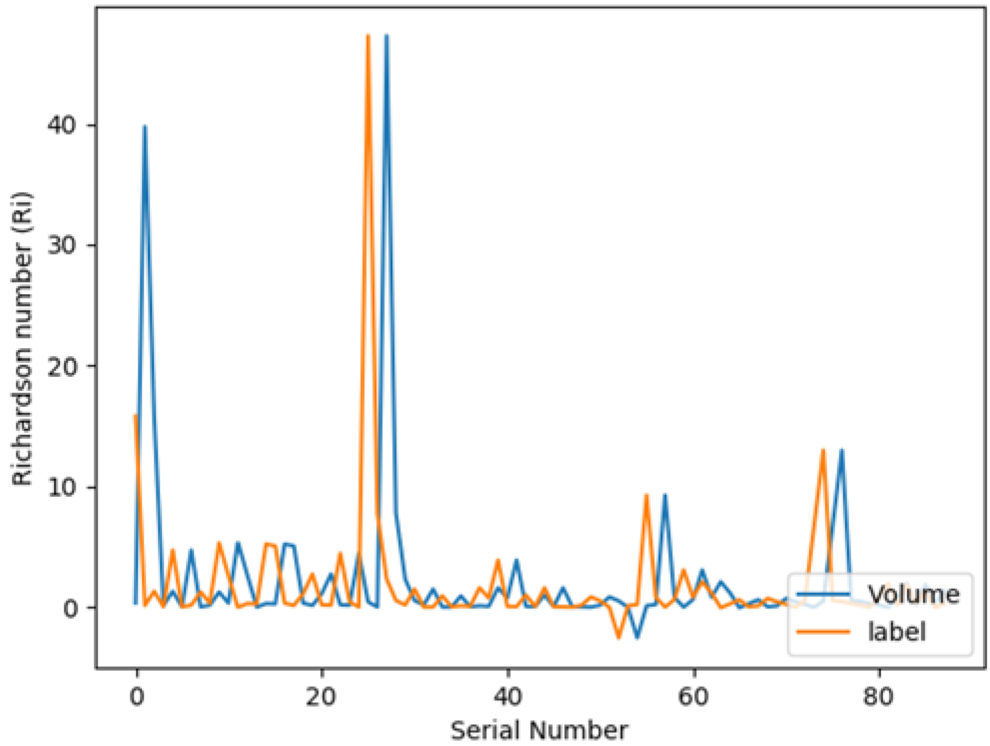

Figure 2. Turbulence forecast on January to March 2018

This is suggestive that seasonality information is necessary to achieve high accuracy rates to forecast the average monthly Richardson number value. The accuracy to forecast the Richardson Number values by SVM is -9.40308708894586 %

4. Conclusions

Compare with the empirical result we have successfully demonstrated that the degree of atmospheric stability condition in layer 300 m using gradient Richardson number value for a synoptic hour in 0000H and the machine learning techniques by SVM can result in accurate predictor for forecasting the average Richardson number value on the turbulence forecasting for period January to March 2018.

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