A real-time data association of internet of things based for expert weather station system

Indrabayu[1], Intan Sari Areni[2], Anugrayani Bustamin[1], Rizka Irianty[1]
[1]Department of Informatics Engineering, Hasanuddin University, Makassar, Indonesia
[2]Department of Electrical Engineering, Hasanuddin University, Makassar, Indonesia

Article Info	ABSTRACT
	The wind carries moisture into an atmosphere and hot or cold air into a climate, affecting weather patterns. Knowing where the wind is coming from gives essential insight into what kind of temperatures are to be expected. However, the wind is affected by spatial and temporal variabilities, thus making it difficult to predict. This study focuses on finding data associations from the weather station installed at Hasanuddin University Campus based on internet of things (IoT) using Raspberry Pi as a gateway that associated all the meteorological data from sensors. The generation of association rules compares the apriori and FP-growth algorithms to determine relations among itemsets. The results show that high humidity and warm temperature tend to associate with a westerly wind and occur at night. In contrast, conditions with less humid and moderate temperatures tend to have southerly and southeasterly wind.
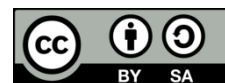
Corresponding Author:

Indrabayu
Department of Informatics Engineering, Hasanuddin University
Jl. Poros Malino KM. 6, Bontomarannu, Gowa, South Sulawesi 92172, Indonesia
Email: indrabayu@unhas.ac.id

1. INTRODUCTION

The pattern of weather changes in an area is determined by several variables, including the location and geographic shape of the region. Indonesia is a tropical country with a diverse climate and is strongly influenced by rainfall patterns [1]. The high rainfall in the tropics is caused by several interrelated factors, such as the inter-tropical convergence zone (ITCZ), Indonesian throughflow (ITF), El-Niño Southern Oscillation (ENSO), Pacific decadal oscillation (PDO), Indian ocean dipole mode (IODM), and madden julian oscillation (MJO) [2]. Moreover, tropical cyclones, storms characterized by low atmospheric pressure, strong winds, are also known to cause extreme rain events in Indonesia [3]. All regions in Indonesia are predicted to experience changes in rainfall patterns [4]. In addition, changing trends can show significant variations for monthly, seasonal, and even annual timescales [5]. This variation makes the weather in Indonesia fluctuating and difficult to predict. Extreme weather changes will cause losses in various aspects of life. Therefore, weather forecasting technology is urgently needed and continues to be developed with an increasingly high level of accuracy.

In [6]–[8] has developed a weather forecasting system for long-term prediction by utilizing artificial intelligence. Some institutions and companies even have their weather stations to collect weather data and predict upcoming weather events. This data is used for their purposes, and in some cases, shared between third parties. In this case, the weather station used is professional and expensive, so it is not affordable for small companies [9].

Some fields require short-term forecasts for specific local areas, such as agriculture, construction, air travel and transportation, and solar power generation. The importance of these predictions is increasing, especially in the industrial sector. Many authors have developed short-term weather forecasting systems, mainly using artificial intelligence and data mining approaches to make predictions [10]–[12]. Meanwhile, some authors also use internet of things (IoT) technology and Raspberry Pi to create monitoring systems to gain information about environmental conditions on a more local level [13]–[15]. The systems could monitor surrounding weather conditions such as humidity, temperature, soil moisture, rainfall, and light intensity. The association between the rain-determining parameters can be used as an initial analysis in this study.

To overcome this problem, the authors' in 2020 built a prototype of a low-cost mini weather station based on artificial intelligence for temporal and spatial data collection, which is used for short-term predictions [16]. As a further step from previous research, this study aims to determine the association between temperature and humidity with wind direction in Gowa Regency, Indonesia, because wind direction is one of the significant indicators in weather prediction. Weather data is obtained from low-cost weather stations that utilize the IoT technology. This research begins a temporal-based association system development for temperature, humidity, and wind direction parameters. The association of these parameters can be used as a reference for the intensity of the movement of the wind direction to temperature and humidity in Gowa Regency, South Sulawesi. This research will continue to be developed by adding other parameters that affect short-term weather forecasts.

Two popular association algorithms are used to determine the association between temperature, humidity, and wind direction parameters, namely the apriori algorithm and FG-growth. Both algorithms have been applied in various fields, such as disaster management [17], medical [18], industry [19], education [20], [21], and weather prediction [22]. The advantage of the apriori algorithm is its capability to significantly reduce the itemset's size in the database as it focuses on generating and discovering the most frequent itemsets. It is also easy to implement and study because the data structure is straightforward. Apriori's limitation has required a scan of the database at every level of the breadth-first search to create the candidate itemsets and calculate the corresponding support count. Apriori will be inefficient when memory capacity is limited with many transactions. It also necessitates the user's setting to the minimum support count and minimum confidence. Due to the uncertainty of the underlying associate rules of the original data, the two values above set by the users may not be proper [23], [24]. Based on these problems, FP-Growth was also developed to find the association relationship of weather parameter data. Thus, the performance of the two algorithms will be compared to find the optimal solution. After the association stage, as the additional contribution of the research, identification, and analysis of time patterns were carried out using the temporal association rule (TAR). The structure of this paper is as. In section 2, the research method and methodology stages are described. In section 3, the results are discussed. And finally, section 4 concludes the paper and discusses future work.

2. RESEARCH METHOD

The weather station [16] is built through a Raspberry Pi circuit and long range (LoRa) hat and gateway. Meteorological sensors are interconnected with the LoRa shield as nodes. A Raspberry Pi Type B model is embedded in the LoRa Hat board to facilitate long-range data transmission. Nodes Censors comprises DHT22 for temperature and humidity measurement, anemometer to calculate the wind speed with wind vane sensors to identify the wind direction. An Arduino Mega Microcontroller 2,560 is used to read and process the data from node censors. IP channel is previously determined to allow LoRa Fat to find the data. Upon retrieval into the Raspberry Pi, the data is then added to the local database with a timestamp. The weather station can operate approximately 5-10 meters with the height of installation 20 meters above the ground, which can be seen in Figure 1. The association algorithm's implementation in this study is used to see the effect of patterns based on the temporal analysis. The research stages in Figure 1 consist of data collecting from the low-cost weather stations and data analysis with association algorithms. Winds bring humidity into the atmosphere and hot or cold air into the climate, affecting weather patterns. Hence, a change in wind results in a change of weather. Identifying the direction of the wind provides essential insight into the type of temperature to expect. Temperature and humidity are essential parameters in looking at the relationship between weather patterns.

2.1. Data collection

This research used data from a low-cost weather station that has been built in [19]. The input data were obtained from the weather station's sensor readings for temperature, humidity, and wind direction. Data collection on weather stations is taken every 5 minutes during December 2019 in Gowa Regency, South Sulawesi Indonesia.

2.2. Data preprocessing

The preprocessing stages consist of data selection, interpolation, normalization, and categorization. This stage selects relevant data to be processed into the system so that the data do not contain noise and do not have a NULL value (missing value). There are 1,261 selected data from 1,440 raw data that will be interpolated to eliminate missing data from the built weather station. The following process is normalization to scale the attribute values of data in a specific range. In this study, the min-max normalization method was used. Before implementing the Association Rules algorithm, the data is categorized in the weather categorization stage based on conditions in the Gowa region. The normalized temperature, humidity, and wind direction data will be categorized into different intervals as shown in Tables 1 to 3, respectively.
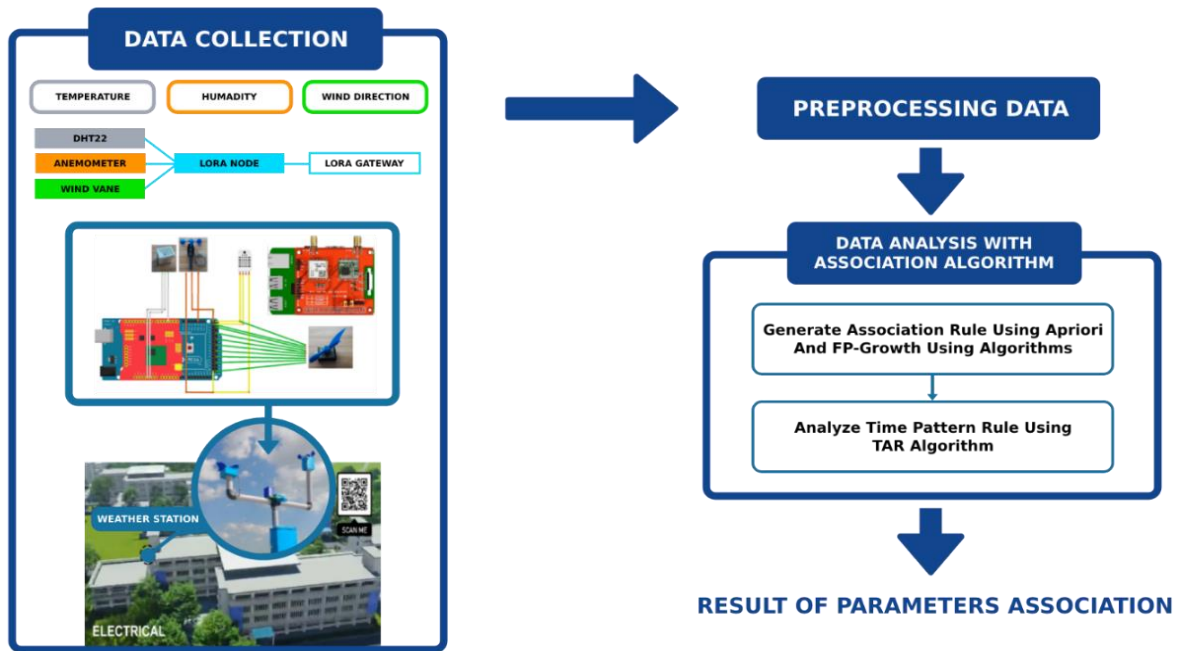

Figure 1. The real-time weather station

Table 1. Categorization of temperature data

Rating	Value (°C)
Higher	>35
Moderate	28-34
Lower	21-27
Lowest	14-20

Table 2. Categorization of relative humidity

Rating	Value (%)
Humid	>80
Less Humid	50-79
Less Dry	0-49

Table 3. Categorization of wind direction

Category	Direction (°)
North	0
North - East	45
East	90
South - East	135
South	180
South - West	225
West	270
North - West	315

2.3. Data analysis with association algorithms

Association rule mining (ARM) is a prominent and well-explored method for determining relations among itemsets in large databases. It was initially introduced for discovering regularities between products in large-scale transaction data recorded by point-of-sale (POS) systems in supermarkets [25]. The discovered connections between different itemsets are presented in the form of association rules. The basic formula of association rules is **A→B**, which represents the portion of the transaction containing **A** that also contains **B**. It is the conditional probability of the consequent given the antecedent [21]. The popular ARM algorithms are apriori, eclat, dclat, FP-tree growth, H-Mine, FIN, AprioriTID, and RElim [26].

Association rule mining works in two parts. First, all frequent itemsets are generated. These are sets of items that have at least the given minimum support. In the second step, association rules are generated from the frequent itemsets found in the first step [27]. The importance of these rules is usually measured by two metrics, support, and confidence. Support is the proportion of transactions in the database in which item A appears. Support shows the popularity of an item and can be used to filter out items with low occurrences. Confidence signifies the likelihood of item B being purchased when item A is purchased. It is the conditional probability of occurrence of the consequent given the antecedent. The user defines the minimum threshold value for support and confidence to eliminate less frequent rules [28]. The minimum value identifies how often the itemset appears, or what is known as the minimum support threshold (MST) is set at 0.5. Meanwhile, the minimum confidence threshold (MCT) states that the minimum value of confidence from the resulting relationship items is set at 0.7.

$$Support(A) = \frac{Num.\,of\ transaction\ in\ which\ A\ appears}{Total\ num.\,of\ transaction} \tag{1}$$

$$Confidence(A \rightarrow B) = \frac{Support(A \cup B)}{Support(A)} \tag{2}$$

Besides *Support* and *Confidence*, the association rule also has a *Lift* ratio, which is also a measure to determine its significance. The *Lift* ratio shows the reality of the data association between parameters. *Lift* > 1 indicates a positive association between the formed itemsets. This value also indicates the validity of an association rule as shown in (3).

$$Lift\ (A \rightarrow B) = \frac{Confidence(A \cup B)}{Support\ (A) * Support(B)} \tag{3}$$

2.3.1. Apriori algorithm

Apriori is an algorithm for finding frequent itemsets from a dataset by generating a candidate key that uses prior knowledge of recurring itemset properties. It searches for a series of frequent sets of items in the datasets and builds associations and correlations between the itemsets. The apriori algorithm is described as [29].

Algorithm apriori
```
Cₖ: Candidate itemset of k
Lₖ: frequent itemset of size k
L₁: {frequent itemset};
for (k=1: Lₖ != θ; k++) do begin
Cₖ₊₁ = candidates generated from Lₖ;
for each transaction t in database do{
increment the count of all candidates in Cₖ₊₁ that are contained in t
Lₖ₊₁ = candidates in Cₖ₊₁ with min_support
}
End
Return UₖLₖ;
```

2.3.2. Frequent pattern (FP) growth algorithm

The FP-Tree works by overlapping itemsets that share the same prefix path, making the data set's information highly compressed. It scans the database only twice, and it does not need any candidate generation. In the first scan, the algorithm finds the support values for each item. It will discard the infrequent itemsets and sort the itemsets in decreasing order based on their supports. Then, it creates the FP-tree in the second scan. The tree's root is labeled with null, while the tree nodes represent each transaction's items, which are marked with the item's name and a counter. The nodes are linked one after the other in the order of their support values. Different transactions can have overlapped paths when they share items (when they have the same prefix). In this case, the counters are incremented. Otherwise, it will create new nodes

when there are no overlapped items. Finally, frequent itemsets are extracted from the FP-Tree by reading it from the last node to root (bottom-up method) [30].

2.3.3. Temporal association rules

Based on Figure 1, after the preprocessing is done, the next step is to implement the data into the apriori association rule algorithm and FP-growth. The two classical methods in the association rule can only identify some patterns that occur frequently. Data from a weather station is temporal data. Using this method is not enough. A priori or FP-growth with the temporal association rule (TAR) analysis is expected to provide information on the relationship between weather data variables accompanied by time scale parameters. The frequent itemset obtained from the algorithm will generate rules that meet the specified minimum support and confidence. The implementation of TAR into these two methods also uses these parameters only with the time dimension's involvement so that the formula indicates the support and confidence obtained from a priori and FP-growth.

3. RESULTS AND DISCUSSION

Based on the implementation of the two algorithms, five rules are obtained, according to Table 4. The formation of association rules of the two algorithms used involves the values of support and confidence. The results shown in Table 4 are the rules with the highest confidence value from combinations of itemsets that often occur in weather station data. Apart from confidence, the lift is also used to see the validity of the resulting rules. This lift ratio shows the reality of the data relationship between parameters. Lift >1 indicates a positive association relationship between the formed itemsets. For Rule 1, the same confidence value is obtained from testing with apriori and FP-Growth. However, the resulting lift value is different even though it shows a positive association between the Humid, LowerTemp, and NorthWest wind direction categories. The temporal feature was obtained 16 hours in two different time ranges, which are 00.00-08.00 and 15.00-23.00. If observed from the lift ratio generated in Table 4, the data's duration with the most number gives a small lift value. The period for the frequency of the data itemset does not occur on the same day. In contrast, rule 5 gives high lift values of 17.27 for FP-growth and 2.45 for apriori. The pattern of data frequency in the 11.00-15.00 time period is consistently obtained every day with a duration of 4 hours.

Table 4. Rules generation by the apriori and FP-Growth algorithm

No	Generate Rule	Apriori		FP-Growth		Time Period
		Confidence	Lift	Confidence	Lift	
1	Humid, LowerTemp → NorthWest	0.98	1.66	0.98	2.78	00.00-08.00 15.00-23.00
2	LessHumid, ModerateTemp → SouthEast	1	2.45	1	12.12	13.00-17.00
3	Humid, LowerTemp → West	0.98	1.68	1	8.63	00.00-08.00 19.00-23.00
4	LessHumid, ModerateTemp → South	0.98	2.36	1	6.82	11.00-20.00
5	LessHumid, ModerateTemp → SouthWest	1	2.45	1	17.27	11.00-15.00

The knowledge representation formed from the five association rules in Table 1 shows that the wind direction tends to blow to the west with very high humidity (Humid) level between 50-70% range and warm temperatures between 21-27 °C that occurs mostly at night. As for the average conditions during the day, the wind direction tends to the South and Southeast with a high humidity level (LessHumid) and moderate temperature. This phenomenon is implying for Gowa Regency, South Sulawesi. Figure 2 shows the relationship between wind direction and the number of data itemset frequencies.

Figure 2 shows the northwest wind direction's high probability with lower temperature and humid conditions during the data collection period. Although these conditions are often found, other associated conditions are formed with the two algorithms used, as shown in Table 4. As is well known, one of the conditions that affect temperature and humidity is wind. The duration of air mass movement that occurs due to differences in air pressure between two locations can affect wind direction changes. Westerly winds generally influence the wind direction in December in Indonesia.

The existing conditions for the area under review in December provide the same facts as the tested association system results. The northwest monsoon has high humidity, moderate temperature and the average wind movement tends to dominate from north to south [31]. The association relationship that is formed can be a reference for rainfall around the area in terms of both relationships between weather parameters and the duration of occurring weather conditions.
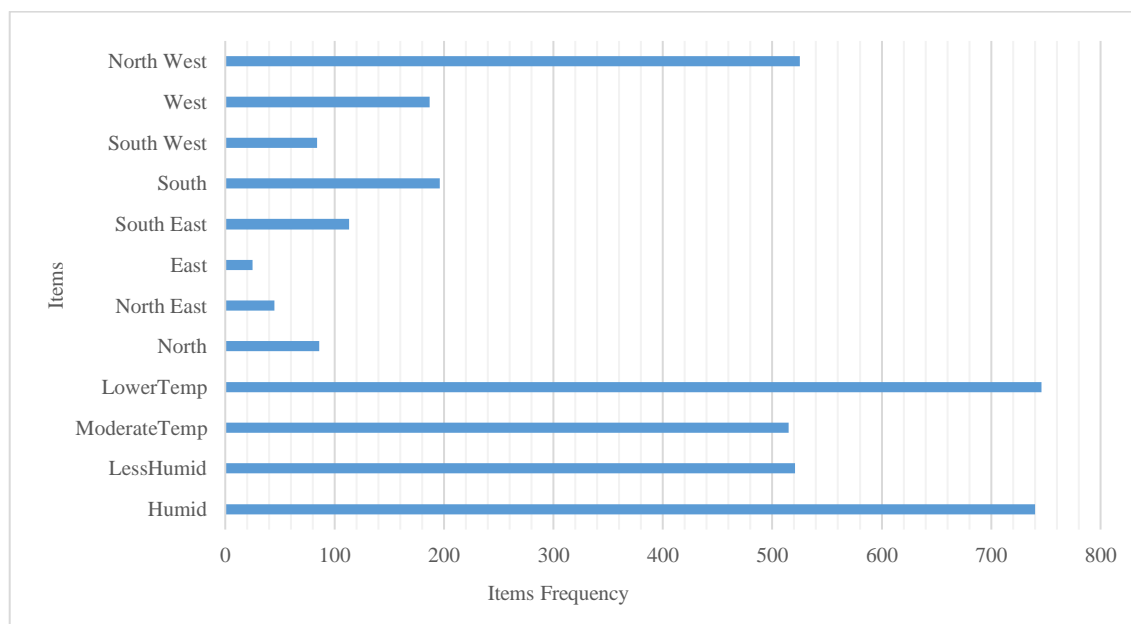
Figure 2. Interpretation of item relationships and the number of data itemset frequencies

4. CONCLUSION

This study uses FP-Growth and apriori association rules to find associations between weather parameters in Gowa City. The weather data is obtained from a low-cost weather station. With MST and MCT set at 0.5, five association rules are obtained. The results show a positive association between humidity, temperature, and wind direction. At night, the wind dominantly blows to the west with a very high humidity level between 50-70% and warm temperatures between 21-27 ℃. During the day, the wind direction tends to the South and Southeast with high humidity and moderate temperature. In the future, this research can be developed with more complete weather indicators such as associations of temperature, humidity, wind direction, wind speed, and rainfall to get better prediction results. Besides, the prediction process can also be optimized with other algorithms that can provide better short-term temporal prediction results.

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BIOGRAPHIES OF AUTHORS

Indrabayu 🆔 🇬 SC Ⓟ was born on July 16, 1975 in Makassar, Indonesia. He was awarded Summa Cum Laude from the Doctoral degree in Artificial Engineering in Civil Application from Hasanuddin University, Makassar, Indonesia, in 2013. Also received M.E. degree in multimedia and communication from Institut Teknologi 10 November, Surabaya, Indonesia in 2005. His research interest includes artificial intelligence and multimedia processing. He can be contacted at email: indrabayu@unhas.ac.id.

Intan Sari Areni ⓘ 🖼️ SC Ⓟ was born in Watampone, South-Sulawesi, Indonesia, 1975. She received a B.E. and M.E. degree in Electrical Engineering from University of Hasanuddin (UNHAS) Makassar (1999) and University of Gadjah Mada (UGM) Jogjakarta (2002), respectively, and received a Doctorate degree from Ehime University Japan in 2013. Since 2000 she has been in the Electrical Engineering Department, Faculty of Engineering UNHAS as a lecturer. Her research interests in Multimedia Signal Processing, Telecommunication, Wireless and Biomedical Engineering, Powerline Communication System (PLC). She can be contacted at email: intan@unhas.ac.id.

Anugrayani Bustamin ⓘ 🖼️ SC Ⓟ was born in Sengkang, 1 December 1990. Graduated S1 Informatics Engineering majors on Universitas Hasanuddin, Makassar. In 2014 continuing education in Informatics Engineering Study Program, Department of Electrical Engineering, Universitas Hasanuddin, Makassar, Indonesia. Member of Artificial Intelligence and Multimedia Processing (AIMP) Research Group, Universitas Hasanuddin. Her research interests include speech recognition and natural language processing. She can be contacted at email: anugrayani@unhas.ac.id.

Rizka Irianty ⓘ 🖼️ SC Ⓟ was born in Makassar, 20 November 1997. She studied Informatics Engineering in Universitas Hasanuddin and graduated in 2019. She is a part of Artificial Intelligence and Multimedia Processing (AIMP) research group at Universitas Hasanuddin and her research interest includes computer vision and image processing. She can be contacted at email: rizkairianty@gmail.com.