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Image Classification Using Machine Learning Algorithms to Detect Cloud Types

Klasifikasi Gambar menggunakan Algoritma Machine Learning untuk Mendeteksi Jenis Awan

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Abstract

Study of atmospheric are currently growing rapidly to analyze the negative effects of climate change, weather and air quality. Unstable atmospheric conditions have a negative impact, as extreme weather. The combination of technology and analysis of atmospheric conditions is currently developing rapidly. While atmospheric research using machine learning technology and algorithms is advancing swiftly, challenges persist in identifying the optimal machine learning model for precise cloud type classification. The application of Machine Learning algorithms in atmospheric research has been widely carried out to predict wind direction and cloud imagery to detect weather using satellite data. Detecting cloud type is important for predicting the upcoming weather. However, to detect the type of cloud, it is necessary to choose the algorithm with the best performance. This study applies the Convolutional Neural Network (CNN) with EfficienNetB3 method, Support Vector Classifier (SVC), XGBoost Classifier (XGB), Extra Tree Classifier (ETC), Random Forest (RF), and Decision Tree (DT) algorithms in classifying cloud images to detect clouds type. The method used in this research involves an experimental approach in the hope of gaining a deeper understanding of the factors that influence the performance of machine learning models in classifying cloud types. The dataset used in this research is 1500 cloud data (1200 training data, 300 testing data). Researchers conducted a comparison of algorithms to find out the best algorithm performance in classifying cloud type images. The results showed that doing the CNN algorithm showed better performance with an average accuracy got of 81.03% compared to the SVC algorithm (34.44%), XGB (33.79%), ETC (39.25%), RF (36.18), and DT (29.35%). Our contribution to this research is that we compare machine learning algorithms to detect cloud types along with the impact and characteristics of cloud types from the prediction results.

Keywords: image classification, cloud types, comparison, machine learning.

Abstrak

Kajian atmosfer saat ini berkembang pesat untuk menganalisis dampak negatif perubahan iklim, cuaca dan kualitas udara. Kondisi atmosfer yang tidak stabil memberikan dampak negatif, seperti cuaca ekstrem. Kombinasi teknologi dan analisis kondisi atmosfer saat ini berkembang pesat. Meskipun penelitian di atmosfer yang menggunakan teknologi dan algoritme pembelajaran mesin berkembang pesat, tantangan tetap ada dalam mengidentifikasi model pembelajaran mesin yang optimal untuk klasifikasi jenis cloud yang tepat. Penerapan algoritma Machine Learning dalam penelitian atmosfer telah banyak dilakukan untuk memprediksi arah angin dan citra awan untuk mendeteksi cuaca menggunakan data satelit. Mendeteksi jenis awan penting untuk memprediksi cuaca yang akan datang. Namun untuk mendeteksi jenis cloud perlu dipilih algoritma dengan performa terbaik. Penelitian ini menerapkan algoritma Convolutional Neural Network (CNN) dengan metode EfficienNetB3, algoritma Support Vector Classifier (SVC), XGBoost Classifier (XGB), Extra Tree Classifier (ETC), Random Forest (RF), dan Decision Tree (DT) dalam mengklasifikasikan cloud. gambar untuk mendeteksi jenis awan. Metode yang digunakan dalam penelitian ini melibatkan pendekatan eksperimental dengan harapan mendapatkan pemahaman yang lebih mendalam tentang faktor-faktor yang mempengaruhi kinerja model machine learning dalam mengklasifikasikan jenis awan. Dataset yang digunakan dalam penelitian ini adalah 1500 data cloud (1200 data pelatihan, 300 data pengujian). Peneliti melakukan perbandingan algoritma untuk mengetahui kinerja algoritma terbaik dalam mengklasifikasikan citra tipe cloud. Hasil penelitian menunjukkan bahwa pengerjaan algoritma CNN menunjukkan kinerja yang lebih baik dengan perolehan rata-rata

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akurasi sebesar 81.03% dibandingkan dengan algoritma SVC (34.44%), XGB (33.79%), ETC (39.25%), RF (36.18), dan DT (29.35). %). Kontribusi kami pada penelitian ini adalah kami membandingkan algoritma machine learning untuk mendeteksi jenis awan dengan disertai impact dan karakteristik jenis awan dari hasil prediksi.

Kata kunci: klasifikasi gambar, jenis cloud, perbandingan, pembelajaran mesin.

1. Introduction

Atmospheric stability is a very important issue in predicting weather [1]–[3]. Unstable atmospheric conditions have a negative impact on the form of extreme weather [4], climate change [5], and air quality [6]. Weather prediction can reduce negative effects if proper preparations are made for bad weather [7]. In Indonesia, weather prediction information can be got by monitoring the website and social media of the Meteorology, Climatology and Geophysics Agency (BMKG). BMKG is an institution that aims to carry out observations, analyzes and services in weather, climate and earthquakes [8]. Weather predictions informed by BMKG are information got from an analysis of weather phenomena that have already occurred and generate opportunities for phenomena to occur again, combined with cloud analysis from satellite imagery [9]. Cloud analysis studies are carried out to observe cloud types and produce information on weather phenomenon opportunities [10]. To find out the clouds, a classification method used to classify cloud types based on the physical characteristics of the clouds got from satellite imagery [11]. Proper model testing needs to be done to classify cloud types to produce better predictions.

As technology develops, the classification of cloud types has become one of the fastest growing research areas in the world. One technology used in cloud type classification is image classification [12]. By implementing image processing, image processing to detect, measure, and identify cloud types is done automatically. One application of technology to classify cloud types is machine learning technology [12]– [14]. Machine Learning (ML) is a discipline from the branch of artificial intelligence that aims to make machines learn and develop from data to help humans decide using the implementation or development of algorithms. The application of ML with a collection of cloud data taken from satellite imagery enables direct cloud monitoring and potential real-time weather information. There is research that has developed cloud type classification technology based on ML models with better accuracy than traditional methods [15]. However, research regarding the selection of a good ML algorithm for detecting cloud types has not been carried out by many researchers.

One of the ML algorithms, i.e., the Convolutional Neural Network (CNN), is proven to classify cloud types with good accuracy results above 80% [16]– [18]. Good accuracy shows how well the model produces predictions of cloud types according to actual cloud types. However, CNN is not the only ML model can classify cloud types. Another study implemented a Support Vector Classifier (SVC) [19] with an accuracy of 93%. Other algorithms, such as XGBoost Classifier (XGB) [20], Extra Tree Classifier (ETC) [21], Random Forest (RF) [22], and Decision Tree (DT) [23] although there has been no research using these algorithms to detect cloud types, but these algorithms have good accuracy in classifying images with an accuracy of over 90%. These results show that the ML algorithm produces relatively good accuracy in classifying images.

In summary, tackling the challenge of image-based cloud type classification involves employing state-of-the-art approaches, utilizing Convolutional Neural Network (CNN) with the EfficientNetB3 method as the primary model. EfficientNetB3, renowned for its optimal balance between efficiency and high performance, plays a crucial role in extracting complex features from images. Additionally, the Support Vector Classifier (SVC) enhances the strategy by focusing on the formation of an optimal hyperplane for class separation. The classification model gains strength through the integration of the XGB, ETC, RF and DT. A comparative analysis of these diverse algorithms facilitates a comprehensive approach to navigating the complexity of cloud-type image classification, with each algorithm contributing to the overall performance of the classification model. This strategy represents recent progress by juxtaposing the reliability of CNNs with the effectiveness of classical classification algorithms, thereby enhancing accuracy in cloud type detection tasks.

Our study of the application of the ML algorithm in classifying images made us interested in comparing the CNN, SVC, XGB, ETC, RF, and DT algorithms in classifying images for detecting cloud types. This research finds out the best algorithm for detecting cloud types. The novelty in this study is that we used the EfficienNetB3 method, which is a large family of CNN and we have not found that this method is used for the classification of cloud types. The results of the accuracy of the ML algorithm in past research to classify images became our basis for selecting the algorithms for our comparison. The comparative measurement indicators that we use are accuracy, recall, precision, and F1-Score.

2. Research Methods

The cloud type detection method used in this study uses several ML algorithms, i.e., CNN, SVC, XGB, ETC,

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RF, and DT algorithms. The cloud image data that we use in this study is the Howard-Cloud-X [24] with a total of 1500 data (1200 are used for training data and 300 data are used for data testing). Analysis of ML algorithm models using accuracy, recall, precision, and F1-Score measurements.

2.1. System Overview

Pre-implementation of ML algorithms, cloud image preprocessing carried out in this study aims to convert image data into arrays. The data array is used for learning ML algorithms. Next, the array data is extracted to retrieve the characteristics of the objects in each type of cloud. These characteristics are used for the image classification process which aims to predict cloud types. The next step is to split the dataset with a ratio of 80:20 between training data and testing data. The dataset which has been divided into training and testing data, is processed by ML algorithms, i.e., CNN, SVC, XGB, ETC, RF, and DT algorithms. The analysis conducted in this study uses the Python programming language. The learning outcomes carried out by each ML algorithm on cloud type data sets produce different accuracy. These results are due to the fact that each ML algorithm has a different pattern of learning. To choose the best algorithm for detecting cloud types, it is necessary to evaluate the model with the same indicator measurement standards. Model evaluation can be carried out by considering the resulting accuracy, F1-Score, precision, and recall values. In general, an overview of the process of implementing ML algorithms can be seen in Figure 1.

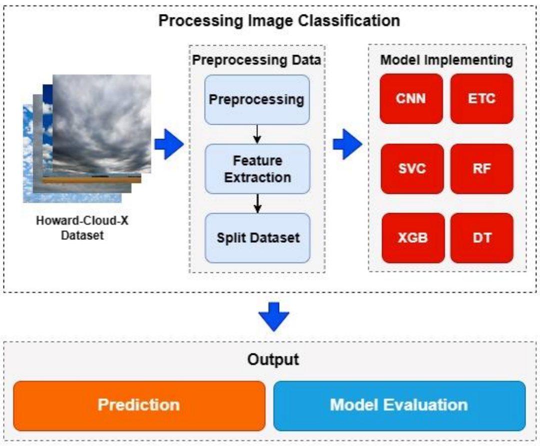

Figure 1. Sample Cloud Types on CCSN Database.

2.2. Preparing Dataset

The classification of cloud types on the Howard-Cloud-X has 10 types of clouds, i.e., Altocumulus, Altostratus, Cirrocumulus, Cirrostratus, Cirrus, Cumulonimbus, Cumulus, Nimbostratus, Stratocumulus, and Stratus.

Figure 2. Sample Cloud Types on CCSN Database. [24]

Figure 2 is an example of different types of physical clouds. The dataset in this study is divided into training data (1200 data) and testing data (300 data). Each type of cloud has different characteristics and impact. For example, cloud color, cloud brightness, cloud shape, and cloud thickness. In addition to different characteristics, cloud types can be used as weather predictions that will occur in the near future. The types of weather are sunny, cloudy, storm, and rainy [25]. Rainy weather is divided into several characteristics, i.e., light rain, moderate rain, heavy rain, very heavy rain, and extreme rain [26]. The ML algorithm identifies cloud photos and generates an impact shortly in the form of weather. We write more complete information about the characteristics and impacts of clouds in Table 1.

Table 1. Impact And Characteristic Cloud Types

Cloud Types	Description	
Altocumulus	Impact	Heavy rain accompanied by lightning
	Characteristic	Flat like a wad of pale white cotton and consists of water droplets with a temperature of about 10 degrees
Altostratus	Impact	Light rain
	Characteristic	The color is bluish and the shape is like fibers
Cirrocumulus	Impact	Storm
	Characteristic	Light clouds, sometimes patchy, like sheets. Sometimes it looks like it's full of ripples or made of tiny grains
Cirrostratus	Impact	Storm
	Characteristic	Thin white clouds that covered the entire sky like a veil
Cirrus	Impact	Bright
	Characteristic	Very high clouds, white, and looks very thin
Cumulonimbus	Impact	The rain was very heavy to the extreme

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Cloud Types	Description	
	Characteristic	Clouds with flat shapes, described as very dark walls, tall, large, and dense
Cumulus	Impact	Sunny, if developed will produce light rain
	Characteristic	Clouds like cotton or cauliflower float in the air.
Nimbostratus	Impact	Light to heavy rain
	Characteristic	Dark grey clouds seemed to fade into rain.
Stratocumulus	Impact	Sunny to light rain
	Characteristic	Roll-shaped clouds that vary in color from gray to bright white, with patches of bright gaps from the sun
Stratus	Impact	Sunny to Drizzling
	Characteristic	Clouds in the form of sheets that are layered, or shaped like fog.

2.3. Preparing Algorithm

Since each algorithm possesses distinct characteristics, we preconfigured several relevant variables for each algorithm before constructing the model. The configuration details can be observed in Table 2.

Table 2. Preparing Algorithm

Algorithm	Setup	
CNN	Method	EfficienNetB3
	Epoch	5
	Initial Epoch	0
	Learning Rate	7.5f
	Verbose	1
	Batch Size	13
Random Forest	Estimator	10
	Random State	42
XGBoost Classifier	Estimator	10
	Random State	42
Extra Tree Classifier	Estimator	10
	Random State	42
Decision Tree Classifier	Estimator	10
	Random State	42
Support Vector Classifier	Count of Hyperline	10
	Kernel	Linear
	Gamma	Auto

Computing resources used for executing ML algorithms are adjusted so that implementing cloud type classification models is efficient and effective. The combination of 12 GB of RAM and sufficient Python 3, together with the cloud-based computing environment provided by Google Colab, allows us to carry out data processing, model training and evaluation with ease and scalability.

2.4. Convolutional Neural Network (CNN)

The Convolutional Neural Network (CNN) algorithm is a Deep Learning (DL) algorithm that is suitable for classifying images [27]. Judging from the CNN learning pattern, CNN has a complex pattern and has three dimensional layers consisting of width, height, and depth. Each layer is connected via neurons in each layer.

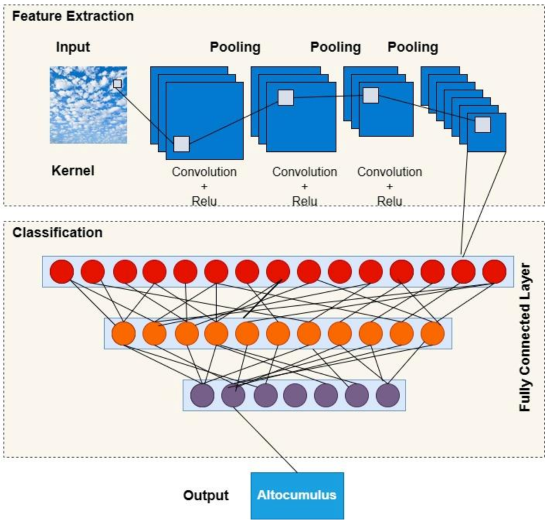

Figure 3. Illustration of CNNclassifying cloud types

Figure 3 shows the implementation of CNN in carrying out the process of classifying cloud types with the output of the classification results being Altocumulus. A series of convolutions with a maximum value is the initial stage before classifying cloud type images. Formula 1 is the way to get a series of convolutions.

$$z^l = h^{l-1} \times W^l \quad (1)$$

The h symbol indicates the maximum value in the layer and W is the layer width. Convoluted cloud type, Max Pooling layer will return the maximum value to the kernel. Furthermore, these values are mapped to features and converted into vectors by giving weights to the matrix. Image classification is carried out by involving neurons as connectors and producing outputs in the form of classification result vectors.

2.5. Random Forest (RF)

The Random Forest (RF) technique is a classification method created by combining decision trees with the random selection of features [28]. Random Forest has also been used to classify cloud types [29], [30]. In order to produce cloud type forecasts using the RF method, scikit-learn (a Python module) utilizes the majority vote of all decision trees. Each decision tree (hx) generates its own cloud type predictions by evaluating the classification outcomes. Every decision tree is computed through Gini Importance, a binary tree consisting of two nodes. The computation of Gini Importance is illustrated in Formula 2.

$$ni_j = w_{left(j)}c_{left(j)} - w_{right(j)}c_{right(j)} \quad (2)$$

ni_j is node j, $w_{left(j)}$ and $w_{right(j)}$ are the number of samples that reach node j from the left and right nodes, $c_{left(j)}$ and $c_{right(j)}$ are the impurity values of node j from the left and right nodes. Furthermore, the

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significant value in each decision tree can be calculated using Formula 3.

$$fi_i = \frac{\sum j{:}node\ j\ splits\ on\ feature\ i\ ni_j}{\sum k \in all\ nodes\ ni_k} \quad (3)$$

fi is the important feature *i*, and *ni* is the important node *j*. Furthermore, the result is normalized to a value between 0 and 1 divided by the sum of all the feature importance values ($normfi_i$). To calculate it can be seen in Formula 4.

$$normfi_i = \frac{fi_i}{\sum j \in all\ features\ fi_j} \quad (4)$$

The last step calculates the average across all trees with the total value of important features in each tree ($normfi_{ij}$) divided by the number of trees (*T*). RF calculations can be seen in Formula 5.

$$RF = \frac{\sum j \in all\ trees\ normfi_{ij}}{T} \quad (5)$$

2.6. XGBoost Classifier (XGB)

XGBoost, or Extreme Gradient Boosting, is a machine learning algorithm utilized for data classification and regression. It adopts an ensemble learning method to amalgamate multiple basic models into a more sophisticated and precise one [31]. XGBoost enhances the gradient boosting algorithm by introducing several additional features, including regularization and handling of missing values. It also employs a gradient descent technique in the structure of decision trees, which accelerates the training process of the model. XGBoost has been shown to be effective in various data science competitions and is regarded as one of the most advanced machine learning algorithms currently available.

2.7. Extra Tree Classifier (ETC)

The Extra Tree Classifier (ETC) is a machine learning technique that leverages a highly randomized tree structure, much like Random Forest (RF), to analyze datasets associated with cloud types. In ETC, each decision tree is trained using all available cloud type images and tested with a random sample that includes k-features, with the aim of achieving optimal prediction and accuracy. To use ETC for cloud type prediction, the first step involves calculating the entropy value, which reflects the degree of homogeneity in class distribution within a set of objects. The entropy value is directly proportional to the degree of homogeneity in the class distribution of cloud images. Formula 6 can be utilized to determine entropy values in decision trees.

$$Entropy\ (S) = \sum_{i=1}^{0} P_i \log 2^{P_i} \quad (6)$$

The sample subset is represented by P_i and *i* represents an attribute value. The next step is to make a feature selection that shows random variable knowledge. The higher the feature selection value (Gain) got shows the better ETC produces predictions. To get the Gain value, use the following Formula 7.

$$Gain(S, A) = \sum_{v \in V(A)} \frac{|S_v|}{|S|} Entropy(S_v) \quad (7)$$

2.8. Support Vector Classifier (SVC)

In the current study, the Support Vector Classifier (SVC) is utilized for cloud type detection, and it operates by applying a kernel that aims to identify hyperplanes (separators) capable of maximizing the margin distance between classes. SVM is a classification method that divides data into two distinct groups, and in this particular scenario, the objective is to differentiate between 10 different types of clouds. Therefore, SVM can be leveraged to categorize clouds into 10 distinct classes using 10 separating hyperplanes. Each hyperplane will segregate the two different cloud classes and maximize the margin or distance between them. Ultimately, SVM will seek the hyperplane with the maximum margin, which can effectively separate the 10 types of clouds. Formula 8 provides a method to compute the hyperline.

$$w \,.\, x_i + b = 0 \quad (8)$$

Formula 5 utilizes *w* to denote the model parameters, *x* to represent the attribute values, and *b* to represent the bias scalars employed in tea leaf disease analysis

2.9. Decission Tree (DT)

The Decision Tree technique for classifying cloud types is a machine learning algorithm that predicts the class of incoming data based on existing features. This method creates a decision tree based on the values of the features in the data. Each branch on the decision tree represents the value of those features, and each node represents a decision based on the rules used to separate data into different classes of cloud types. The first step in building a decision tree is to identify the most significant features in distinguishing data classes. Then, rules for separating the data into these classes are formulated based on the feature values. Each of these rules represents a node in the decision tree. The Decision Tree algorithm then selects the next feature to be compared, and this process continues until all data is separated into different classes. Eventually, a decision tree will be constructed that can be used to predict cloud-type classes.

2.10. Model Evaluation

The performance evaluation of the ML algorithm for identifying cloud types in this study involves four metrics: accuracy, F1-Score, precision, and recall. The accuracy metric represents the percentage of correctly predicted cloud types based on the actual types. The F1-Score is a measure that combines precision and recall to provide an average comparison between the two. The precision metric indicates the accuracy of positive

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predictions of cloud types, where the number of correct predictions is compared to the total number of data classified as positive for cloud types in the test dataset. To compute these metrics, both correct and incorrect predictive values are required. Formulas 9 to 12 show the computation for accuracy, F1-Score, recall, and precision.

$$Accuracy = \frac{(TP+TN)}{(TP+FP+FN+TN)} \tag{9}$$

$$F1 - Score = 2 \times \frac{Recall+Precision}{Recall \times Precision} \tag{10}$$

$$Recall = \frac{TP}{TP+FN} \tag{11}$$

$$Precision = \frac{TP}{TP+FP} \tag{12}$$

These formulas utilize the variables TP, TN, FP, and FN. TP represents the total number of correctly classified positive cloud types according to actual data. TN represents the total number of correctly classified negative cloud types according to actual data. FP represents the total number of falsely classified positive cloud types despite being negative in actual data. Finally, FN represents the total number of falsely classified negative cloud types despite being positive in actual data.

3. Results and Discussions

The examination of the cloud type classification outcomes in this research is divided into two sections, specifically the classification outcomes and the efficacy of every ML algorithm, along with metrics for evaluating accuracy, F1-Score, precision, and recall.

3.1. Results

The results of the comparison of ML algorithms for detecting cloud types in this study prove that the sensitivity of each model is different and produces different outputs. In this study, the CNN algorithm has the best sensitivity compared to other algorithms in detecting cloud types. The CNN algorithm with EfficientNetB3 method obtains a model accuracy of 81.03%. Other ML algorithms can be said to be insensitive to cloud-type datasets. We conclude these results after we carry out model testing on cloud type datasets, other ML algorithms (SVC, XGB, ETC, RF, and DT algorithms) get model accuracy below 40%. In this study, the SVC algorithm obtained an accuracy of 34.4%, the XGB model accuracy was 33.79%, the ETC model accuracy was 39.25%, the RF model accuracy was 36.18%, and the DT model accuracy was 29.3%. The performance of the ML algorithms carried out in this study can be seen in Table 3.

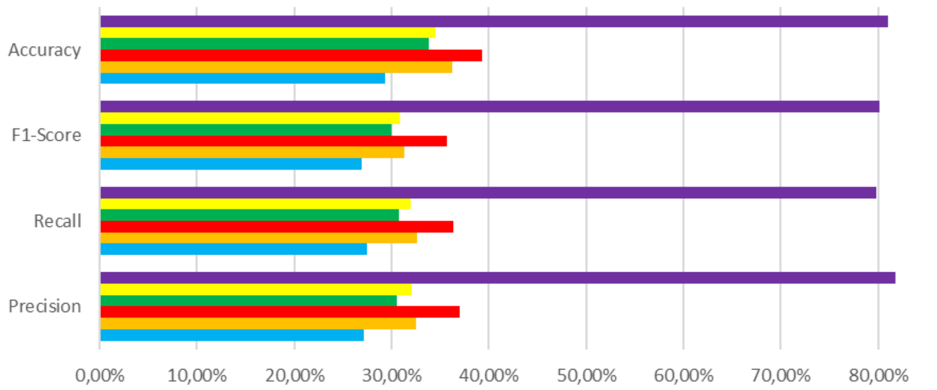
Table 1. Results and Model Testing

Model	Cloud Types	A	F	R	P
CNN	Altocumulus	81.0%	75.3%	70.9%	80.4%
	Altostratus		88.8%	93.8%	84.4%
	Cirrocumulus		78.4%	87.7%	70.9%
	Cirrostratus		72.4%	72.1%	72.8%
	Cirrus		81.1%	73.0%	91.2%
	Cumulonimbus		83.3%	80.0%	86.9%
	Cumulus		86.6%	91.4%	82.3%
	Nimbostratus		82.3%	77.3%	89.1%
	Stratocumulus		76.9%	85.9%	69.7%
	Stratus		76.2%	66.0%	90.2%
SVC	Altocumulus	34.4%	19.6%	15.6%	26.3%
	Altostratus		50.0%	65.7%	40.3%
	Cirrocumulus		25.5%	20.6%	33.3%
	Cirrostratus		31.2%	43.4%	24.3%
	Cirrus		28.5%	25.0%	33.3%
	Cumulonimbus		32.2%	33.3%	31.2%
	Cumulus		54.3%	52.3%	56.4%
	Nimbostratus		36.0%	37.9%	34.3%
	Stratocumulus		18.1%	13.6%	27.2%
	Stratus		13.3%	12.5%	14.2%
XGB	Altocumulus	33.79	11.7%	9.38%	15.7%
	Altostratus		63.8%	78.9%	53.5%
	Cirrocumulus		22.7%	17.2%	33.3%
	Cirrostratus		18.1%	21.7%	15.6%
	Cirrus		26.0%	25.0%	27.2%
	Cumulonimbus		32.7%	33.3%	32.2%
	Cumulus		53.0%	52.3%	53.6%
	Nimbostratus		35.7%	34.4%	36.0%
	Stratocumulus		29.2%	27.2%	31.5%
	Stratus		7.27%	8.33%	6.45%
ETC	Altocumulus	39.25	26.8%	28.1%	25.7%
	Altostratus		64.7%	86.8%	51.5%
	Cirrocumulus		27.9%	20.6%	42.8%
	Cirrostratus		26.0%	26.0%	26.0%
	Cirrus		34.0%	33.3%	34.7%
	Cumulonimbus		31.0%	30.0%	32.1%
	Cumulus		55.7%	52.3%	59.4%
	Nimbostratus		40.0%	34.4%	47.6%
	Stratocumulus		21.7%	22.7%	20.8%
	Stratus		29.1%	29.1%	29.1%
RF	Altocumulus	36.1%	16.0%	12.5%	22.2%
	Altostratus		61.6%	86.8%	47.8%
	Cirrocumulus		25.4%	24.1%	26.9%
	Cirrostratus		18.1%	21.7%	15.6%
	Cirrus		32.4%	25.0%	46.1%
	Cumulonimbus		40.7%	36.6%	45.8%
	Cumulus		59.7%	61.9%	57.7%
	Nimbostratus		16.6%	13.7%	21.0%
	Stratocumulus		25.5%	27.2%	24.0%
	Stratus		17.3%	16.6%	18.1%
DT	Altocumulus	29.3%	13.7%	12.5%	15.3%
	Altostratus		52.8%	60.5%	46.9%
	Cirrocumulus		23.5%	20.6%	27.2%
	Cirrostratus		20.4%	21.7%	19.2%
	Cirrus		23.2%	20.8%	26.3%
	Cumulonimbus		28.5%	26.6%	30.7%
	Cumulus		41.0%	38.1%	44.4%
	Nimbostratus		28.5%	31.0%	26.4%
	Stratocumulus		14.6%	13.6%	15.7%
	Stratus		23.3%	29.1%	19.4%

Table 3 shows that the CNN algorithm is the most sensitive in classifying cloud images among other algorithms. The other algorithms exhibit poor sensitivity towards cloud type datasets.

3.2. Discussion

In this study found that all tested algorithms have good sensitivity in detecting Altostratus cloud types compared to other types. This result is based on the recall values, where all algorithms scored recall values above 60% in detecting Altostratus clouds. Recall values indicate the model's capability to recognize and locate all positive objects in the cloud type dataset. Although the other cloud types exhibit very low accuracy, precision, and F1-Score on all algorithms except CNN, Altostratus clouds have distinct cloud characteristics that are suitable for ML algorithms to learn from.



	Precision	Recall	F1-Score	Accuracy
CNN	81,79%	79,81%	80,13%	81,03%
SVC	32,08%	31,99%	30,87%	34,44%
XGB	30,50%	30,77%	30,01%	33,79%
ETC	36,97%	36,33%	35,69%	39,25%
RF	32,52%	32,61%	31,33%	36,18%
DT	27,15%	27,45%	26,95%	29,35%

Figure 4. Average Value on Measurement Indicators of Machine Learning Models in Detecting Cloud Types

The CNN algorithm with the EfficientNetB3 method has the highest average value for all measurement indicators (accuracy, F1-Score, precision, and recall) with an average accuracy of 81.03%, F1-Score of 80.13%, precision of 81.79%, and recall of 79.81%. In comparison to all other algorithms, the DT algorithm is the least effective in detecting cloud types, as evidenced by the average value of all indicators obtained being below 30%. While other algorithms also have poor sensitivity to cloud-type datasets, the average measurement indicator value obtained is still above 30%.

To conclude the overall results, the average values of F1-Score, precision, and recall have been computed and are presented in Figure 4. From the results presented, CNN with the EfficienNetB3 method is proven to handle cloud image patterns better than other algorithms. The reason is that CNN has many layers and complex feature extractors so that it can recognize cloud image data well during the training process. Other algorithms have limitations in understanding the relationship between features and image data of cloud types, which causes low performance in detecting cloud types.

4. Conclusion

According to the results of this study, it can be concluded that the CNN algorithm with the EfficienNetB3 method demonstrated the best model performance in classifying cloud image types compared to other machine learning algorithms. The average accuracy obtained by the CNN algorithm was 81.03%, which was significantly higher than the other algorithms tested, such as SVC (34.44%), XGB (33.79%), ETC (39.25%), RF (36.18%), and DT (29.35%). These findings suggest that the CNN algorithm is the most appropriate algorithm for detecting cloud types, particularly Altostratus clouds, due to its high sensitivity to cloud-type datasets. To sum up, this study has successfully compared the performance of various machine learning algorithms in classifying cloud image types, and the results highlight the superiority of the CNN algorithm. These findings have significant implications for future research on cloud classification using machine learning algorithms. Based on these findings, it is recommended that future studies should focus on enhancing the performance of the CNN algorithm by exploring new feature extraction techniques and utilizing deep learning approaches. Furthermore, it is suggested that future research should consider expanding the dataset to include a more diverse range of cloud types and weather conditions to improve the generalizability of the results. Finally, it is proposed that future studies should investigate the potential application of machine learning algorithms for other meteorological applications, such as weather forecasting and climate change monitoring.

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