

## ACCREDITATION PREDICTION OF EARLY CHILDHOOD EDUCATION INSTITUTIONS USING MACHINE LEARNING TECHNIQUES

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### Abstract

Accreditation is an acknowledgement of an educational institution regarding the feasibility of carrying out the educational process. Making predictions can save time for early childhood education institutions in compiling accreditation forms that will be submitted. Prediction in determining accreditation becomes an important lesson for an institution in self-assessing the quality of its services. Choosing which method to use in the accreditation prediction process becomes a serious problem, so the prediction results can be the closest or most accurate. Machine Learning is an application that is part of Artificial Intelligence which is widely used in prediction research. In this experiment, three algorithms in machine learning are tested, namely SVM, KNN and ANN. This study uses data from the accreditation results of early childhood education institutions in South Kalimantan; the sample data is 75%, and the remaining data is 25%. The results of the KNN algorithm with Euclidean distance and the number of neighbours 5 have the best performance in predicting the value of the accreditation predicate compared to other methods. The results of calculations using the KNN method produce Area Under Curve values of 1,000, CA 1,000, F1 1,000, precision 1,000 and Recall 1,000.

**Keywords** : Accreditation, Artificial Neural Network, Early Childhood Education, K-Nearest Neighbors, Support Vector Machine.

## 1. INTRODUCTION

Accreditation is a determination from a third party related to formal evidence that a conformity assessment agency has the competence to carry out certain conformity assessment tasks [1]. Institutions that carry out accreditation are called accreditation bodies. Accreditation is part of the government's obligation to determine whether an educational unit is appropriate for access by the public [2]. This is important so that people do not choose the wrong quality institution. Empirically for more than 30 years, NAEYC has accredited and set standards for early childhood education units. NAEYC accreditation helps parents find the best early childhood experiences for their children. *The National Association for Early Childhood Education (NAEYC)* is the largest non-profit association in the United States that represents early childhood education [3]. *The NAEYC* has established 10 standards for early childhood programs to help families make the right choice when looking for a daycare center, preschool, or kindergarten [4].

In Indonesia, PAUD accreditation is carried out by BAN PAUD and PNF. Current empirical conditions show that many early childhood education institutions are moving towards

industrialization of education and prioritize profits. Improving education for the people of Indonesia will spur the achievement of other goals and objectives, especially increasing the human development index (IPM). The role of education is expected to increase Indonesia's competitiveness in supporting SDGs 2030. PAUD as a fundamental education which is the initial foundation for the quality of child development is very important to underlie further education, including increasing HDI [6].

Predictions in determining accreditation are an important lesson for an institution in self-assessing the quality of its services [7] and [8]. Making predictions can save PAUD institutions time in compiling accreditation forms to be submitted [9]. With the predicted results, institutions can improve accreditation, namely: by improving accreditation instruments and data and information collection instruments, preparing all accreditation documents and accreditation supporting information, preparing documents, school accreditation, and appointing teachers who are more professional in PBM to be assessed. Accreditation assessors complete school facilities and infrastructure, decorate the accreditation assessment room as attractive as possible, and invite the school committee on the accreditation assessment day.

*SVM* is one of the best methods that can be used in prediction problems. The *SVM* concept originates from the two-class prediction problem which requires positive and negative training sets [16]. *SVM* tries to find the best *hyperplane* (separator) to be separated into two classes and maximize the margin between the two classes [17] and [18]. In some cases, *SVM* is proven to have high prediction accuracy. For example, the wear prediction model for abrasive tools with the results of wear experiments shows the prediction accuracy of the *IHDGWO-SVM model* is 92% [19]. The prediction of curvature and uniformity coefficients in unsaturated laterite soils treated with hybrid cement composites and nanostructured mine granules, the results are 97% close to accurate [20]. Predictive model for coronary artery disease with an accuracy of 88% [21]. *SVM* algorithm with 95% accuracy for earthquake early warning prediction models [22]. Accuracy is above 95% for prediction of cardiac stroke [23].

*ANN* or artificial neural network is one of the artificial representations of the human brain which always tries to simulate the learning process in the human brain. The human brain contains millions of nerve cells (*neurons*) that process information. Each cell interacts with each other to support the working ability of the brain. Each nerve cell will have a cell nucleus which is responsible for processing information. According to information from existing research and journals, *the ANN Prediction Method* is widely implemented in scientific analysis methods. An example of an *ANN* implementation that is often used in forecasting and prediction. Research results [24] Gold price prediction in the Indian commodity market with the best MPA results obtained is given by the *GDM\_LCH* method with an accuracy value of 92.4%. A network model (*ANN*) to predict the modulus of elasticity (*MOE*) of *BWC* with an accuracy value of 98% *MAPE* so that it can track the quality of *BWC* in the production process [25]. *ANN* analyzes the data, determines how much water has been applied to irrigation systems in India, and predicts the results to manage water savings [26]. *The A DEA-ANN* model can estimate teaching efficiency in Canadian universities. Prediction results with *ANN* can maximize initial predictive power [27].

*K-Nearest Neighbor (KNN)* is an algorithm for classifying data on an object based on some *K training* data that has the closest distance or closest neighbor to the object [9]. *KNN* is used to classify new objects based on attributes and training data samples [28] and [29], following the *KNN algorithm formula*: (a) *Proximity* is usually 0-1, (b) 0 means the case is not very good. Similar, whereas for one means very similar cases. In research, *KNN* can predict accurately. Prediction of multiplication errors in multiplication errors, classification assignments in the Data-Driven System with 97%

accuracy results [30]. The test for predicting heart disease with *KNN* provides a predictive yield of 69% [31] and an accuracy of 67% [32]. This paper proposes predicting the accreditation of *PAUD* institutions with three algorithms, namely *Support Vector Machines (SVM)*, *Artificial Neural Networks (ANN)* and *K-Nearest Neighbor (KNN)*. The data used comes from 225 institutions in South Kalimantan. The proposal with these three algorithms aims to test which algorithm is most appropriate for predicting accreditation scores

## 2. RESEARCH METHODS

The research methodology consists of collecting datasets, building classification models, training classification models, testing, and calculating performance. Figure 1 shows the flow of the research methodology.

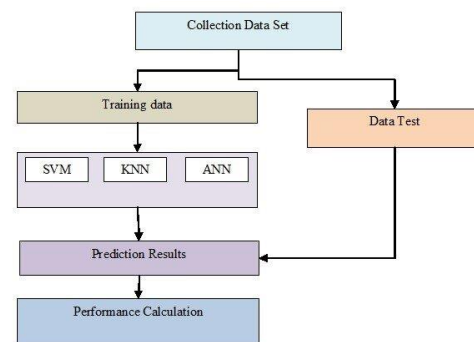


Figure 1. Research Stages

### 2.1 . Collection of Data Sets

The dataset used is data from the accreditation results of early childhood education institutions in South Kalimantan which consist of public kindergartens, private kindergartens and play groups. The amount of data used was 225 institutions, with details of the training data used as many as 200 institution data and test data used as many as 25 institution data. Data was collected using online techniques by accessing <https://gratis.banpaupnf.or.id/data/0/150000> [33].

### 2 .2. Formation of Predictive Models

At this stage, each algorithm is configured using several parameters. The aim is to determine the effect of parameters on the performance of machine learning algorithms that take labeled data as input and produce better accuracy in predicting the accreditation results of early childhood education institutions.

### 2 .3. Support Vector Machine (SVM)

The basic concept of *SVM* is actually a harmonious combination of computational theories that existed decades before, such as hyperplane

margining which is similar to other concepts [34]. SVM is a machine learning algorithm that uses a technique by taking labeled data as input and producing better accuracy in prediction and regression problems [35].

SVM concept can simply be explained as an effort to find the best *hyperplane that functions as a separator for two classes in the input space* [36] and [37]. A pattern that is a member of two classes: +1 and -1. Patterns belonging to class -1 are denoted in red (square), while patterns in class +1 are denoted in yellow (circle). The classification problem can be translated by trying to find the line (hyperplane) that separates the two groups. Various alternative dividing lines (discrimination boundaries). Available data is denoted while  $x_i \in \mathbb{R}^d$  each label is denoted  $y_i \in \{-1, +1\}$  for  $i = 1, 2, \dots, l$ , where  $l$  is the number of data. It is assumed that the two classes -1 and +1 can be completely separated by the defined dimensional hyperplane :

$$w \cdot x + b = 0 \quad (1)$$

$w$  = Normal terrain  
 $b$  = Plane position relative to the coordinate center

Patterns  $x_i$  that belong to class -1 (negative sample) can be formulated as patterns that fulfill the inequality :

$$w \cdot x + b \leq -1 \quad (2)$$

Currently  $x_i$  belonging to class +1 (positive sample )

$$w \cdot x + b \geq 1 \quad (3)$$

The largest margin can be found by maximizing the value of the distance between the hyperplane and its closest point, which is  $\frac{1}{\|w\|}$ . This can be formulated as a Quadratic Programming problem [37], namely finding the minimum point of equation (4), taking into account the limits of equation (5).

$$w \rightarrow \min_{\tau} \tau (w) = \frac{1}{2} \|w\|^2 y_i (w \cdot x + b) \geq 0, \forall_i$$

This problem can be solved by various computational techniques, including lagrange multipliers [38].

$$L(w, b, \alpha) = \frac{1}{2} \|w\|^2 - \sum_{i=1}^l \alpha_i (y_i (w \cdot x + b) - 1)$$

Where  $\alpha_i$  is the Lagrange multiplier, which is zero or positive ( $\alpha_i \geq 0$ ). The optimal value of equation (6) can be calculated by minimizing  $L$  to  $w$  and, maximizing  $L$  to  $\alpha_i$ . Taking into account the property that at the optimal gradient point  $L = 0$ , equation (5) can be modified as a maximization problem that contains only  $\alpha_i$ , like equation (6) below.

Maximize: (6)

$$\sum_{i=1}^l \alpha_i - \frac{1}{2} \sum_{i=1}^l \sum_{j=1}^l \alpha_i \alpha_j y_i y_j x_i \cdot x_j$$

Subject to (7)

$$\alpha_i \geq 0 \quad (i = 1, 2, \dots, l) \quad \sum_{i=1}^l \alpha_i y_i = 0$$

From the results of this calculation obtained mostly positive. Data that is correlated with  $\alpha_i$  this positive one is called a support vector.

### 2.3. K-Nearest Neighbor (KNN) Algorithm

*K-Nearest Neighbor (KNN)* algorithm is a method for classifying objects based on learning data closest to objects [39] and [40]. Learning data is projected into a multidimensional space, where each dimension represents a feature of the data. This space is divided into sections based on the classification of learning data [41]. A point in this space is marked as class  $c$  if class  $c$  is the most common classification found in the  $k$  nearest neighbors of that point. Near or far neighbors are usually calculated based on Euclidean distance with the formula as in equation (8).

$$distance = \sqrt{\sum_{x=1}^n (x_{training}^i - x_{testing})^2}$$

Where :

$x_{training}^i$  = training data to -  $i$ ,  
 $x_{testing}$  = data testing  
 $i$  = the  $i$ th (row) record of the table,  
 $n$  = amount of training data

At the learning stage, this algorithm only performs feature vector storage and classification of learning data. In the classification stage, the same features are calculated for the test data (whose classification is unknown) [42]. The distance from this new vector to all learning data vectors is calculated, and the nearest  $K$  number is taken. It is estimated that the newly classified points will be included in the most classification of these points. The best  $K$  value for this algorithm depends on the data. In general, a high  $K$  value reduces the effect of noise on classification, but makes the boundaries between each classification more blurred. A good  $K$  value can be selected by parameter optimization, for example by using cross validation. The special case where the classification is predicted based on the nearest learning data (in other words,  $K = 1$ ) is called the algorithm nearest neighbor algorithm [43].

*KNN* algorithm is greatly influenced by the presence or absence of irrelevant features, or if the weight of these features is not equivalent in relevance to the classification [44]. The *KNN* algorithm has several advantages, namely robustness to training data with a lot of noise and is effective when the training data is large. While the weakness

of KNN is that KNN needs to determine the parameter value K (number of nearest neighbours), training based on distance is not clear which distance should be used and what attribute should be used to get the best. results, and computational costs are quite high because calculations are required. the distance from each query instance to the entire training sample. K-Nearest Neighbor (KNN) is a method that uses a supervised algorithm where the results of a new query instance are classified based on the majority of categories in the KNN. The goal of this algorithm is to classify new objects based on attributes and training samples. The classifier does not use any model to match and is based solely on memory. Given a query point, it will search for a number of K objects or (training points) that are closest to the query point. The classification uses the most votes among the K object classifications. The KNN algorithm uses the neighbor classification as the predictive value of the new query instance.

**2.4. Artificial Neural Network (ANN) Algorithm**

Artificial Neural Network (ANN ) can independently define its parameters. ANN or Artificial Neural Network was first discovered by McCulloch and Pitts in 1943. McCulloch and Pitts concluded that combining several simple neurons into a nervous system would increase its computational ability [45] . The weights in the network proposed by McCulloch and Pitts are arranged to perform simple logic functions. The activation function used is the threshold function [46] .

In general, ANN is formed by a number of neurons as information processing units as basic operations to carry out their functions or tasks. Mathematically, the following equation holds for neurons .

$$\mu_x = \sum_{j=1}^p w_{kj} x_j$$

$$y_k = \varphi(\mu_k - \theta_k)$$

Where  $x_1, x_2, x_3 \dots, x_p$ , is the input signal  $w_{k1}, w_{k2}, w_{k3} \dots, w_{kp}$  is the synaptic weight for the neuron,  $\mu_k$  is the output of the linear combination,  $\theta_k$  is the threshold value,  $\varphi( )$  is the activation function, and is the output signal of the neuron [47] .

**3. RESULTS AND DISCUSSION**

**3.1 . Artificial Neural Network (ANN) Method**

Table 1 presents Accreditation Data for Early Childhood Education Institutions. This can be described regarding the results of the research and tests that have been carried out. In addition, it was also conveyed regarding the discussion of the research and testing that had been carried out.

Table 1. Quantities of Accreditation Data for Early Childhood Education Institutions

Accreditation Predicate				
Amount determined	A	B	C	Total
A	5.0	0.0	0.0	5.0
B	0.0	173.0	0.0	173.0
C	0.0	0.0	47.0	47.0
<b>Total</b>	<b>5.0</b>	<b>173.0</b>	<b>47.0</b>	<b>225.0</b>

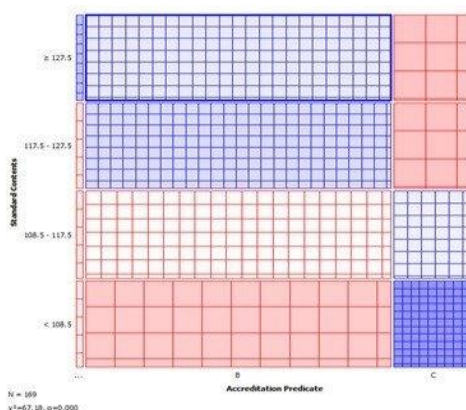


Figure 2. Data Selection Using Widgets

Accreditation results data that has gone through the preprocessing stage are then tested to get the best predictive model for accreditation of early childhood education institutions. The prediction model that has been tested and evaluated using the test data set on the orange application. Based on Figure 2 the data selection process using the *t widget* , first select the column whose accreditation predicate is target data, content standards, process standards, graduation standards, teaching staff standards, infrastructure standards, management standards, financing standards and assessment standards with numeric types, features role.(4)

**3.2 . SVM Method Calculation**

The working principle of SVM is based on the *Structural Risk Minimization ( SRM )* principle, which aims to produce the best hyperplane that separates the input space into two classes. In simple terms, the basic principle of this method is a linear classifier or directional grouping, which is then developed so that it can work in linear problems. This principle itself is a good combination or blend of computational theory that has been developing for a long time. before SVM [48] . Figure 3 is an experiment to calculate the predictive value of accreditation using the SVM method using orange software with a value with a cost variable of 1, an epsilon regression loss of 0.10 using the RBF kernel, optimization of the numerical tolerance parameter of

0.0010 and limiting iterations of 100 and the results obtained

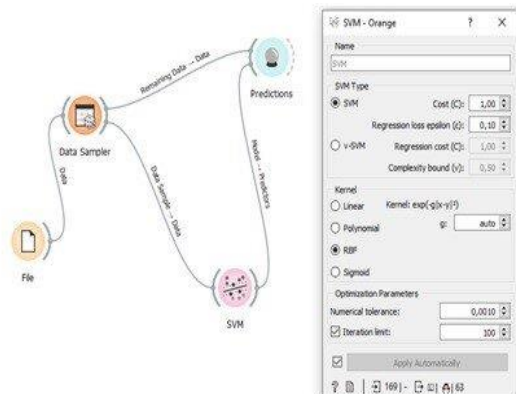


Figure 3. Accreditation prediction model with SVM

Table 2. The results of prediction calculations using the SVM method yield Area Under Curve 1, CA 0.964, F1 0.963, Precision 0.966 and Recall 0.964. Area Under Curve (AUC): is a measure used to evaluate the performance of a classification model. A perfect AUC value is 1, while an AUC value of 0.5 indicates the same model performance as random guessing. In this case, the SVM model produces an AUC value of 1, which indicates that the model has very good performance. CA (Correct Accuracy): is the percentage of correct classification of all observed cases. In this case, the SVM model produces a CA value of 0.964 or 96.4%, which indicates that the model is able to correctly classify 96.4% of all observed cases. F1-score: is the average harmonic measure of precision and recall. The F1-score takes both of these metrics into account and is useful in situations where there is a trade-off between precision and recall. In this case, the SVM model produces an F1-score of 0.963, which indicates that this model has a good balance between precision and recall. Precision: is a measure of how often a model returns true positive results. In this case, the SVM model produces a precision value of 0.966, which indicates that the model has a good ability to predict positive results correctly. Recall: is a measure of how often the model can identify overall positive results. In this case, the SVM model produces a recall value of 0.964, which indicates that the model has a good ability to identify overall positive results.

Table 2 . The results of prediction calculations with the SVM method

AUC	ca	FI	precision	remember
1,000	0.964	0.963	0.966	0.964

### 3.3 . KNN Calculation Method

KNN classifies and predicts objects based on learning data ( *training data* ) that are closest to the

object. The goal of the *KNN algorithm* is to classify new objects based on attributes and samples from the training data. The *KNN* algorithm will find the *k* closest training examples in the feature space and use the average of those closest features to make predictions. Calculation of predictions for accreditation of early childhood education institutions using the *KNN method* using the number of neighbors, five *Euclidian metrics* and uniform weights using the orange application.

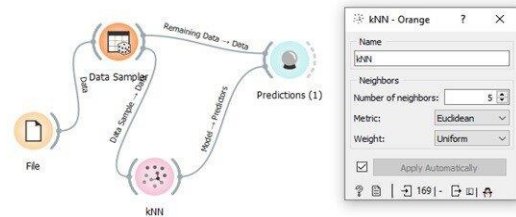


Figure 4. Accreditation Prediction Model with KNN

Table 3 The results of calculations using the *KNN method* yield Area Under Curve values of 1,000, CA 1,000, F1 1,000, precision 1,000 and Recall 1,000.

Table 3 . The results of prediction calculations using the KNN method

AUC	ca	F1	Precision
1,000	1,000	1,000	1,000

Table 3 shows that the results of calculations using the KNN method produce Area Under Curve (AUC), CA, F1, precision, and recall values of 1,000. This shows that the KNN model used is very accurate in predicting the target class. However, to be able to ensure the accuracy of the model, a more complete evaluation needs to be carried out, such as conducting cross-validation and testing on test data that has never been seen before. Apart from that, it is also important to consider other aspects such as the interpretation of the results and the relevance of the model to the problem to be solved. In this case, if the results of further evaluation also show a high level of accuracy, then the KNN model can be considered a good model for predicting classes. target on a given dataset.

### 3.4 Calculation of the Artificial Neural Network (ANN) Algorithm method

Each *ANN model* has an input layer that acts as an information medium in the form of data related to the desired output [49] . This input layer consists of several neurons that represent the variables or parameters needed to solve a problem. The input layer will pass this data to the next neuron in the hidden layer or output layer through a series of weights [50] . This weight is the link from each

neuron to other neurons in the next layer, which will help adapt the ANN structure to a given data pattern by leveraging learning. In the learning process, the weights will be updated continuously until one of the number of iterations, errors and processing time is reached [51]. This is done to adjust the ANN structure to the desired pattern based on certain problems that will be solved using ANN. The next experimental process uses the ANN method with 100 neurons in the hidden layer, relu activation, adam splitting, iteration regularization  $\alpha = 1000$  and the maximum number of iterations is 200, producing the following calculations.

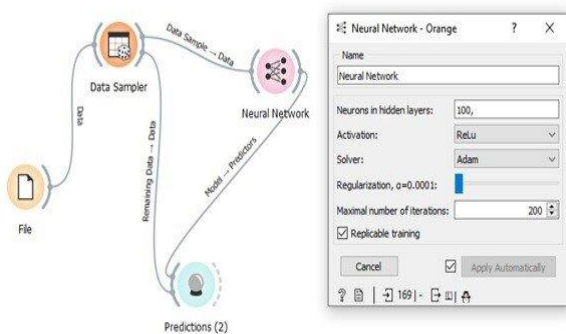


Figure 5. Accreditation Prediction Model with ANN

Table 4 Calculations using the ANN method produce an Area Under Curve value of 0.995, CA 0.964, F1 0.963, precision 0.966 and Recall 0.964.

Table 4. The results of prediction calculations with the ANN method

AUC	ca	FI	precision
0.995	0.964	0.963	0.966

From the calculation results in Table 4, the AUC value of 0.995 indicates that the model has a very good ability to distinguish between positive and negative classes. In addition, the high CA, F1, precision, and recall values also indicate that this model has good performance in making predictions. However, keep in mind that model evaluation results may vary depending on the dataset and evaluation metrics used.

### 3.5 Performance Comparison

Classification performance can be calculated using several formulas. The results can be values for accuracy, precision, and recall, usually expressed as a percentage. Table 5 shows a performance comparison between the KNN, SVM, and ANN algorithms. For the KNN algorithm, this study chose KNN with Euclidean distance and five neighbors, because it has the best performance compared to KNN with other parameters. As for the

SVM algorithm, this study chose SVM with the RBF kernel because it has the best performance among SVM with other parameters. Figure 6 shows a performance comparison graph between the KNN, SVM, and ANN algorithms

Table 5. Prediction Comparison

method	AUC	ca	FI	precision
SVM	1,000	0.964	0.963	0.966
KNN	1,000	1,000	1,000	1,000
ANN	0.995	0.964	0.963	0.966

Table 5 and figure 6 show the results of a performance comparison with the results of the KNN method which is very suitable for predicting accreditation data for early childhood education institutions in South Kalimantan which results in calculating an AUC value of 1,000 CA 1,000 FI 1,000 Precision 1,000 and remembering 1,000. The predicted results of calculations using the KNN method are more accurate than the SVM and ANN methods in the short-term traffic prediction experiment [52], KNN provides more accurate results with an average error proportion of 14.348 and an R-square value of 0.948 compared to SVM and ANN. Research by [53] KNN can recognize symbols from a small sample accurately with a score of 99.8% in a comprehensive study of the various approaches and techniques used to develop sign language lessons. Other related studies have also compared the SVM, KNN and ANN methods, namely research predicting breast cancer detection by [54] where ANN is superior with a predictive value of 97% and SVM 91%. The classification of the ripening level of oil palm with the results using the superior ANN method is 93% [55]. That the prediction model for accreditation of early childhood education institutions needs to be tested using machine learning methods or other prediction techniques.

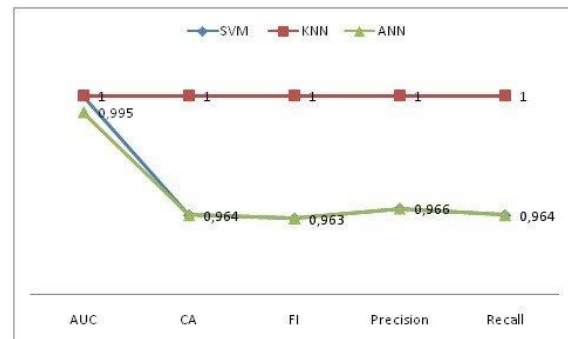


Figure 6. Performance comparison

The K-Nearest Neighbors (KNN) algorithm is a machine learning algorithm used for classification and regression. In simple terms, the KNN algorithm compares new data with existing data in the database. In research on accreditation of PAUD

institutions, the *KNN* algorithm can be used to predict the accreditation of an *PAUD institution* based on the attributes possessed by the institution. On the other hand, Artificial Neural Network (*ANN*) and *Support Vector Machine (SVM)* are also machine learning algorithms that can be used for classification and regression. *ANN* and *SVM* have their own advantages in modeling and predicting data.

The results agree with that in a 2020 study published in the journal "Expert Systems with Applications", the authors compared the performance of *KNN*, *SVM*, and *ANN* in predicting stock prices. The results show that *SVM* has better performance than *KNN* and *ANN* [46] and a 2020 study comparing the performance of *KNN*, *ANN*, and *SVM* in recognizing breast cancer patterns. The results show that *SVM* has better performance than *KNN* and *ANN* [47].

#### 4. CONCLUSION

Accreditation prediction is a useful lesson for early childhood education institutions. With predictions, institutions can assess the quality of their services. By looking at the prediction results, the Institute can improve actual accreditation in the future by improving accreditation instruments and data and information collection instruments, preparing all accreditation documents and other supporting information. If the institution wants the prediction results to be as perfect as possible, then it must carefully consider the algorithmic methodology used during the accreditation process. Machine learning is one of the most widely used applications of AI for learning patterns and making predictions. The results of this experiment evaluate three machine learning algorithms, namely *SVM*, *KNN* and *ANN*. Using data from 75% and 25% of accredited South Kalimantan *PAUD* institutions. The performance of the *KNN* algorithm using Euclidean distance and five neighbors is superior to *SVM* and *ANN*. *KNN* results obtained 100% results with Area Under Curve values (1,000), CA (1,000), F1 (1,000), precision (1,000), and recall (1,000).

By making predictions, institutions can improve actual accreditation in the future by improving accreditation instruments and data and information collection instruments. Machine learning is one of the AI applications that can be used to learn patterns and make predictions, and the experimental results show that the *KNN algorithm* using Euclidean distance and five neighbors is superior to *SVM* and *ANN*. *KNN* results show very good performance with a value of 100% for Area Under Curve, CA, F1, precision and recall. Therefore, using the *KNN algorithm with Euclidean distance and five neighbors* can be used as a recommendation to predict the accreditation of early childhood education institutions in the future.

#### DAFTAR PUSTAKA

- [1] C. D. Diem, P. Darusmiyati, and M. D. Sitinjak, "The Correlation between School Accreditation and Students' English Achievement of Public Senior High Schools," *Stud. Linguist. Lit.*, vol. 5, no. 2, p. p17, 2021, doi: 10.22158/sll.v5n2p17.
- [2] S. A. Makhoul, "Higher education accreditation, quality assurance and their impact to teaching and learning enhancement," *J. Econ. Adm. Sci.*, vol. 35, no. 4, pp. 235–250, 2019, doi: 10.1108/jeas-08-2018-0092.
- [3] C. Boyd-Swan and C. M. Herbst, "Influence of quality credentialing programs on teacher characteristics in center-based early care and education settings," *Early Child. Res. Q.*, vol. 51, pp. 352–365, 2020, doi: 10.1016/j.ecresq.2019.12.013.
- [4] LK Chandler *et al.*, "The Alignment of CEC/DEC and NAEYC Personnel Preparation Standards," *Topics Early Child. Spec. educ.*, vol. 32, no. 1, pp. 52–63, 2012, doi: 10.1177/0271121412437047.
- [5] SN Asiah, "PAUD Management Analysis Based on PAUD Accreditation Standards and PNF in Kutai Kartanegara," *SYAMIL J. Educator. Religion of Islam (Journal Islam. Educ.)*, vol. 6, no. 1, pp. 51–64, 2018, doi: 10.21093/sy.v6i1.1325.
- [6] HR Putera, ZF Ikatrinasari, and HH Purba, "Proposals for Improving Education Services Using the QFD Method with the SERVQUAL Variable Approach," vol. 9, no. 2, 2022.
- [7] J. Sun, Z. Zhang, X. Liu, and H. Zheng, "Reduced Methane Combustion Mechanism and Verification, Validation, and Accreditation (VV&A) in CFD for NO Emission Prediction," *J. Therm. Sci.*, vol. 30, no. 2, pp. 610–623, 2021, doi: 10.1007/s11630-020-1321-3.
- [8] S. D. Mondal, D. N. Ghosh, and P. K. Dey, "Prediction of NAAC Grades for Affiliated Institute with the help of Statistical Multi Criteria Decision Analysis," vol. 1, no. 2, pp. 116–126, 2021.
- [9] L. Genisa and D. I. Mulyana, "Implementasi Penerapan Metode C4.5 dan Naïve Bayes Dalam Tingkat Kelulusan Akreditasi Lembaga PAUD Pada Badan Akreditasi Nasional," *J. Media Inform. Budidarma*, vol. 5, no. 4, p. 1595, 2021, doi: 10.30865/mib.v5i4.3267.
- [10] IK Nti, O. Nyarko-Boateng, FA Adekoya, and BA Weyori, "An empirical assessment of different kernel functions on the performance of support vector machines," *Bull. Electr. Eng. Informatics*, vol. 10, no. 6, pp. 3403–3411, 2021,

- doi:10.11591/eei.v10i6.3046.
- [11] Z. Rustam, F. Zhafarina, JE Aurelia, and Y. Amalia, "Twin support vector machine using kernel function for colorectal cancer detection," *Bull. Electr. Eng. Informatics*, vol. 10, no. 6, pp. 3121–3126, 2021, doi:10.11591/eei.v10i6.3179.
- [12] A. S. R. M. Sinaga, R. E. Putra, and A. S. Girsang, "Prediction measuring local coffee production and marketing relationships coffee with big data analysis support," *Bull. Electr. Eng. Informatics*, vol. 11, no. 5, pp. 2764–2772, 2022, doi:10.11591/eei.v11i5.4082.
- [13] Y. Liang, S. Hu, W. Guo, and H. Tang, "Abrasive tool wear prediction based on an improved hybrid difference grey wolf algorithm for optimizing SVM," *Meas. J. Int. Meas. Confed.*, vol. 187, no. November 2021, p. 110247, 2022, doi:10.1016/j.measurement.2021.110247.
- [14] K. C. Onyelowe, C. B. Mahesh, B. Srikanth, C. Nwa-David, J. Obimba-Wogu, and J. Shakeri, "Support vector machine (SVM) prediction of coefficients of curvature and uniformity of hybrid cement modified unsaturated soil with NQF inclusion," *Clean. Eng. Technol.*, vol. 5, p. 100290, 2021, doi:10.1016/j.clet.2021.100290.
- [15] K. S. Nugroho, A. Y. Sukmadewa, A. Vidiyanto, and W. F. Mahmudy, "Effective predictive modelling for coronary artery diseases using support vector machine," *IAES Int. J. Artif. Intell.*, vol. 11, no. 1, pp. 345–355, 2022, doi:10.11591/ijai.v11.i1.pp345-355.
- [16] J. Song, J. Zhu, and S. Li, "Continuous prediction method of earthquake early warning magnitude for high-speed railway based on support vector machine," *Railw. Sci.*, 2022, doi:10.1108/rs-04-2022-0002.
- [17] H. Puri, J. Chaudhary, K. R. Raghavendra, R. Mantri, and K. Bingi, "Prediction of Heart Stroke Using Support Vector Machine Algorithm," *2021 8th Int. Conf. Smart Comput. Commun. Artif. Intell. AI Driven Appl. a Smart World, ICSCC 2021*, pp. 21–26, 2021, doi:10.1109/ICSCC51209.2021.9528241.
- [18] S. Verma, G. T. Thampi, and M. Rao, "ANN based method for improving gold price forecasting accuracy through modified gradient descent methods," *IAES Int. J. Artif. Intell.*, vol. 9, no. 1, pp. 46–57, 2020, doi:10.11591/ijai.v9.i1.pp46-57.
- [19] G. You, B. Wang, J. Li, A. Chen, and J. Sun, "The prediction of MOE of bamboo-wood composites by ANN models based on the non-destructive vibration testing," *J. Build. Eng.*, vol. 59, no. July, p. 105078, 2022, doi:10.1016/j.job.2022.105078.
- [20] M. N. Amogha Hegde, M. S. Naik, S. N. Chaitra, M. Madhavi, and A. Ravichandra, "Prediction and Analysis of Water Requirement in Automated Irrigation System using Artificial Neural Network(ANN) and Lora Technology," *2021 IEEE Int. Conf. Distrib. Comput. VLSI, Electr. Circuits Robot. Discov. 2021 - Proc.*, pp. 88–92, 2021, doi:10.1109/DISCOVER52564.2021.9663706.
- [21] S. K. Jauhar, "A DEA-ANN-based analytical framework to assess and predict the efficiency of Canadian universities in a service supply chain context," 2022, doi:10.1108/BIJ-08-2021-0458.
- [22] B. Wang and Z. Mao, "A dynamic ensemble outlier detection model based on an adaptive k-nearest neighbor rule," *Inf. Fusion*, vol. 63, no. October 2019, pp. 30–40, 2020, doi:10.1016/j.inffus.2020.05.001.
- [23] H. Ohmaid, S. Eddarouich, A. Bourouhou, and M. Timouyas, "Comparison between svm and knn classifiers for iris recognition using a new unsupervised neural approach in segmentation," *IAES Int. J. Artif. Intell.*, vol. 9, no. 3, pp. 429–438, 2020, doi:10.11591/ijai.v9.i3.pp429-438.
- [24] X. Ding, K. Charlotte, L. Li, and S. X. Ding, "Isolation in Dynamic Systems Using Data-Driven in -Gap Metric based based kNN Algorithm based kNN Algorithm based kNN based kNN," *IFAC Pap.*, vol. 55, no. 6, pp. 169–174, 2022, doi:10.1016/j.ifacol.2022.07.124.
- [25] C. Chethana, "Prediction of heart disease using different KNN classifier," *Proc. - 5th Int. Conf. Intell. Comput. Control Syst. ICICCS 2021*, no. Icccs, pp. 1186–1194, 2021, doi:10.1109/ICICCS51141.2021.9432178.
- [26] K. S. K. Reddy and K. V. Kanimozhi, "Novel Intelligent Model for Heart Disease Prediction using Dynamic KNN (DKNN) with improved accuracy over SVM," *2022 Int. Conf. Bus. Anal. Technol. Secur. ICBATS 2022*, 2022, doi:10.1109/ICBATS54253.2022.9758996.
- [27] "Akreditasi BAN PAUD dan PNF." [Online]. Available: <https://akreditasi.banpaudpnf.or.id/data/0/150000>. [Accessed: 13-Sep-2022].
- [28] I. S. Al-Mejibli, J. K. Alwan, and D. H. Abd, "The effect of gamma value on support vector machine performance with different kernels," *Int. J. Electr. Comput. Eng.*, vol. 10, no. 5, pp. 5497–5506, 2020, doi:10.11591/IJECE.V10I5.PP5497-5506.
- [29] G. V. Gopal and G. R. M. Babu, "An ensemble feature selection approach using



- hybrid kernel based SVM for network intrusion detection system,” *Indones. J. Electr. Eng. Comput. Sci.*, vol. 23, no. 1, pp. 558–565, 2021, doi: 10.11591/ijeecs.v23.i1.pp558-565.
- [30] N. S. A. Yasmin, N. A. Wahab, and A. N. Anuar, “Improved support vector machine using optimization techniques for an aerobic granular sludge,” *Bull. Electr. Eng. Informatics*, vol. 9, no. 5, pp. 1835–1843, 2020, doi: 10.11591/eei.v9i5.2264.
- [31] M. T. Tally and H. Amintoosi, “A hybrid method of genetic algorithm and support vector machine for intrusion detection,” *Int. J. Electr. Comput. Eng.*, vol. 11, no. 1, pp. 900–908, 2021, doi: 10.11591/ijece.v11i1.pp900-908.
- [32] J. Xu, W. Zeng, Y. Lan, J. Guo, and X. Cheng, “Modeling the parameter interactions in ranking SVM with low-rank approximation,” *IEEE Trans. Knowl. Data Eng.*, vol. 31, no. 6, pp. 1181–1193, 2019, doi: 10.1109/TKDE.2018.2851257.
- [33] T. Altalmas, S. Ahmad, N. N. W. N. Hashim, S. S. Hassan, and W. Sediono, “Characteristics with opposite of quranic letters mispronunciation detection: a classifier-based approach,” *Bull. Electr. Eng. Informatics*, vol. 11, no. 5, pp. 2817–2827, 2022, doi: 10.11591/eei.v11i5.3715.
- [34] A. R. Lubis, M. Lubis, and Al-Khowarizmi, “Optimization of distance formula in k-nearest neighbor method,” *Bull. Electr. Eng. Informatics*, vol. 9, no. 1, pp. 326–338, 2020, doi: 10.11591/eei.v9i1.1464.
- [35] M. J. Al Dujaili, A. Ebrahimi-Moghadam, and A. Fatlawi, “Speech emotion recognition based on SVM and KNN classifications fusion,” *Int. J. Electr. Comput. Eng.*, vol. 11, no. 2, pp. 1259–1264, 2021, doi: 10.11591/ijece.v11i2.pp1259-1264.
- [36] N. Qu *et al.*, “Machine learning guided phase formation prediction of high entropy alloys,” *Mater. Today Commun.*, vol. 32, no. April, p. 104146, 2022, doi: 10.1016/j.mtcomm.2022.104146.
- [37] N. Benayad, Z. Soumaya, B. D. Taoufiq, and A. Abdelkrim, “Features selection by genetic algorithm optimization with k-nearest neighbour and learning ensemble to predict Parkinson disease,” *Int. J. Electr. Comput. Eng.*, vol. 12, no. 2, pp. 1982–1989, 2022, doi: 10.11591/ijece.v12i2.pp1982-1989.
- [38] L. Xiong and Y. Yao, “Study on an adaptive thermal comfort model with K-nearest-neighbors (KNN) algorithm,” *Build. Environ.*, vol. 202, no. June, p. 108026, 2021, doi: 10.1016/j.buildenv.2021.108026.
- [39] R. Ma, J. Ban, Q. Wang, and T. Li, “Statistical spatial-temporal modeling of ambient ozone exposure for environmental epidemiology studies: A review,” *Sci. Total Environ.*, vol. 701, p. 134463, 2020, doi: 10.1016/j.scitotenv.2019.134463.
- [40] A. G. Farizawani, M. Puteh, Y. Marina, and A. Rivaie, “A review of artificial neural network learning rule based on multiple variant of conjugate gradient approaches,” *J. Phys. Conf. Ser.*, vol. 1529, no. 2, 2020, doi: 10.1088/1742-6596/1529/2/022040.
- [41] A. Afandi, N. Lusi, I. Catrawedarma, and B. Rudiyanto, “Prediction of Temperature in 2 Meters Temperature Probe Survey in Blawan Geothermal Field Using Artificial Neural Network (ANN) Method,” *SSRN Electron. J.*, vol. 38, no. October 2021, p. 102309, 2021, doi: 10.2139/ssrn.3954816.
- [42] A. Muneer, R. F. Ali, A. Alghamdi, S. M. Taib, A. Almaghthawi, and E. A. Abdullah Ghaleb, “Predicting customers churning in banking industry: A machine learning approach,” *Indones. J. Electr. Eng. Comput. Sci.*, vol. 26, no. 1, pp. 539–549, 2022, doi: 10.11591/ijeecs.v26.i1.pp539-549.
- [43] M. S. Khrisat and Z. A. Alqadi, “Solving multiple linear regression problem using artificial neural network,” vol. 12, no. 1, pp. 770–775, 2022, doi: 10.11591/ijece.v12i1.pp770-775.
- [44] R. Meenal, AI Selvakumar, PA Michael, and E. Rajasekaran, “Sensitivity analysis based artificial neural network approach for global solar radiation prediction in India,” vol. 20, no. 1, pp. 31–38, 2020, doi: 10.11591/ijeecs.v20.i1.pp31-38.
- [45] M. Yanto, S. Sanjaya, Yulasma, D. Guswandi, and S. Arlis, “Implementation multiple linear regression in neural network predict gold price,” *Indones. J. Electr. Eng. Comput. sci.*, vol. 22, no. 3, pp. 1635–1642, 2021, doi: 10.11591/ijeecs.v22.i3.pp1635-1642.
- [46] W. Rizka, U. Fadilah, D. Agfiannisa, and Y. Azhar, “Analysis of PT. Indonesian Telecommunications Using the Support Vector Machine Method,” *Fountain Informatics J.*, vol. 5, no. 2, pp. 2548–5113, 2020, doi: 10.21111/fij.v5i2.4449.
- [47] F. Febrian, “Comparison of Neural Network Classification Techniques, Support Vector Machines, and Naive Bayes in Detecting Breast Cancer,” *BINA Insa. ICT J.*, vol. 7, no. 1, pp. 53–62, 2020.