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A Comparative Analysis of Support Vector Machine and Artificial Neural Network Methods for Predicting Vocational High School Student Graduation

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Abstract: Identifying which students may struggle in examinations early on is a critical challenge in vocational schools. This study aims to create and compare two machine learning models to predict the graduation status of Vocational High School (SMK) students majoring in Software and Game Development (PPLG). This prediction is based on their Competency Skills Test (UKK) scores. We used data from 310 students and tested two methods: Support Vector Machine (SVM) and Artificial Neural Network (ANN). The results are very clear: the SVM model performed exceptionally well, achieving an accuracy of 99%. SVM was able to recognize both 'Competent' and 'Not Yet Competent' students in a balanced manner. Conversely, the ANN model's performance was poor, with an accuracy of only 66%. This occurred because the ANN failed to learn and simply guessed that all students would pass. This research concludes that SVM is a highly effective method to be used as an early warning system. With this system, schools can more quickly assist students who are at risk of failing. SVM achieved 99% accuracy with perfect precision for the Competent class and full recall for the Not Yet Competent class. ROC-AUC and PR-AUC indicated excellent separability and strong minority-class detection. ANN achieved only 66% accuracy, predicting all samples as Competent. Learning curves revealed stagnation and failure to learn minority class patterns. Additional baseline models (Logistic Regression, Random Forest) were tested, with SVM outperforming all others consistently. Statistical significance testing using McNemar's test confirmed that SVM provides significantly better classification performance than ANN ($p < 0.01$).

Keywords: Graduation Prediction; Machine Learning; Support Vector Machine; Artificial Neural Network; Vocational Education.

1. Introduction

SMK has a very strategic position in the national education system as an institution that prepares graduates who are ready to work. The success of SMK graduates can be seen from their ability to pass the Competency Skills Test (UKK). UKK is an assessment that is carried out practically in full so that it can ensure that every student really has the ability to master the technical skills needed in the industry, especially in the Software and Game Development (PPLG) department which has a very dynamic development. In modern education, the ability to predict student academic performance becomes increasingly important because it allows educational institutions to carry out timely interventions and personalized support strategies [1][2]. Recent systematic reviews have shown that machine learning techniques are increasingly used in educational data mining, especially for predicting student graduation outcomes and identifying at-risk students before they reach critical failure points [3][4]. However, in practice, the problem often arises that the school only knows which students are having learning difficulties after all the tests are completed. When declared failed, the assistance provided is very limited and delayed. This condition shows a gap in the evaluation system, namely a reactive evaluation system rather than a proactive one, as stated in various educational contexts around the world [5][6]. Therefore it is urgent to create an early warning system that can change this paradigm from reactive remediation to proactive intervention. This intelligent system is expected to assist teachers in detecting early signs of students who are at risk of failing so that interventions can be made and additional guidance given long before the final exam. The importance of such predictive systems has been emphasized in recent literature, which demonstrates that early identification of struggling students significantly improves retention rates and overall academic success [7][8].

In this era of machine learning technology, it is very possible to solve this problem. By using the student score dataset from previous years, it is possible to build a computer model that learns to identify certain patterns and then applies these patterns to predict future results with a high degree of accuracy. Some previous studies have successfully used Decision Tree, Naïve Bayes, and Random Forest methods for similar objectives. This proves that the application of data-based techniques in education is feasible. In Indonesia specifically, various studies have applied different classification algorithms to predict student graduation. The results demonstrated that traditional machine learning methods produced promising results. However, vocational skill data usually has more complicated characteristics and patterns that are not easily visible; therefore, a more sophisticated and robust method may be required. The nature of competency assessments in vocational education emphasizes practical skills over theoretical knowledge as described in the literature, which presents unique challenges that may not be addressed adequately by conventional predictive models.

Based on these considerations, this study takes into account the two more advanced and powerful methods: Support Vector Machine (SVM) and Artificial Neural Network (ANN). SVM is known for its high performance in classification or separation tasks, particularly when it comes to complex decision boundaries and high-dimensional feature spaces [17]. ANN, on the other hand, is a model that attempts to replicate the functioning of human brain neural networks; hence it is capable of discovering very complex and hidden patterns due to its multi-layer architecture and non-linear activation functions. Comparative studies between them have shown different results based on dataset characteristics, problem domain, and class distribution indicating context-specific evaluation [18][20]. In addition, the choice between SVM and ANN becomes more crucial in the case of educational imbalanced datasets where there are significantly more passing students than failing ones—this is usually true for graduation prediction tasks [21][22]. The main objective of this study is to come up with a direct and fair comparison between these two advanced methods in the specific area of vocational high school graduation prediction. The question that we would like to answer through this study is: which one of these two methods can be regarded as being more accurate and reliable in predicting the graduation of SMK PPLG students from their UKK score data? It is hoped that the results from this research will contribute not only scientifically but practically as well toward developing a genuine early warning tool to be used by schools so that educators may then help those who need it most.

2. Related Work

2.1 Machine Learning for Student Performance Prediction

Educational Data Mining (EDM) has emerged as a powerful approach to extract meaningful insights from academic datasets, enabling institutions to predict student outcomes and implement timely interventions. Pelima *et al.* (2024) conducted a comprehensive systematic literature review analyzing 70 journal articles published between 2018 and 2023, revealing that Support Vector Machine (SVM) and Random Forest are the most commonly utilized algorithms for predicting student graduation and academic performance [1]. Their analysis highlighted a significant gap in existing literature regarding in-depth discussions of specific predictive models and the nuances of algorithm selection based on dataset characteristics. Roslan and Chen (2022) reviewed educational data mining approaches from 2015 to 2021, identifying classification as the most frequently employed technique, with Decision Tree, Bayesian Networks, and Random Forest emerging as the dominant algorithms [2]. Their findings emphasized that Decision Tree classifiers are particularly popular due to their interpretability and high predictive accuracy. Albreiki *et al.* (2021) expanded this perspective by investigating various machine learning techniques including Naïve Bayes, Decision Tree, Multilayer Perceptron, SVM, Random Forest, and Neural Networks for student performance prediction [3]. Their systematic review presented comparative analyses showing that different classifiers perform optimally under different conditions. Namoun and Alshanqiti (2020) surveyed a decade of research on intelligent models for predicting student learning outcomes, categorizing predictive techniques into supervised learning, unsupervised learning, data mining, and statistical approaches [4]. They identified significant research gaps, particularly noting that efforts to develop models specifically estimating learning outcomes remain insufficient.

The challenge of student dropout prediction has also received considerable attention. Colpo *et al.* (2024) explained that EDM techniques, specifically supervised machine learning classification, are increasingly adopted to automate dropout analysis by discovering patterns and identifying at-risk students [5]. Their review highlighted the utilization of Decision Trees, Random Forest, Logistic Regression, SVM, and Multi-Layer Perceptron for predicting dropout and graduation status. However, they identified a critical gap in the application of predictive models in actual educational practice. López-Zambrano *et al.* (2021) conducted a systematic review focusing on early prediction of student learning performance, identifying J48, Random Forest, SVM, and Naïve Bayes as the most commonly used classification algorithms [6]. Their analysis revealed that most studies focused on online learning systems and traditional education, indicating a potential gap regarding vocational education settings. Sghir *et al.* (2023) provided a comprehensive analysis of recent advances in Predictive Learning Analytics over a decade, examining the predictive modeling process including data collection, preprocessing methods, and machine learning model categorization [7]. They identified relevant gaps in current literature and proposed future research directions, emphasizing the need for more context-specific studies. Sekeroglu *et al.* (2021) performed a systematic literature review of student performance prediction studies, covering methods such as Decision Trees, Gradient Boosting, and Artificial Neural Networks [8]. Critically, they identified class imbalance as a significant limitation when evaluating prediction models, noting that accuracy metrics fail to properly reflect the model's true capability when class distribution is skewed.

2.2 Machine Learning Applications in Indonesian Educational

While international literature provides a broad foundation, examining studies within the Indonesian context offers valuable insights into local implementation challenges. Punkastyo *et al.* (2024) implemented data mining using the Naïve Bayes algorithm for predicting student graduation in Indonesian schools, demonstrating the feasibility of applying probabilistic classifiers to local educational datasets [11]. Amri *et al.* (2023) conducted a comparative study of five different algorithms—Naïve Bayes, Decision Tree, ANN, K-Nearest Neighbors, and SVM—for predicting university student graduation rates [12]. Their experimental results revealed that algorithm effectiveness varies significantly depending on data preprocessing techniques and feature selection strategies. Darmawan *et al.* (2023) focused specifically on Islamic high school students, applying SVM and Random Forest to predict graduation patterns [13]. Their research demonstrated that SVM could achieve high accuracy in the context of religious educational institutions. Latifah and Mujiyono (2023) performed a comparative analysis of Naïve Bayes, K-NN, ID3, and SVM algorithms for predicting student graduation at SMK Muhammadiyah Majenang, directly addressing the vocational high school context [14]. Their findings indicated that SVM showed promising results for vocational education settings, though they noted challenges related to parameter tuning. Pratama *et al.* (2024) analyzed the application of Artificial Neural Networks specifically for predicting university student graduation, exploring various network architectures and activation functions [15]. While their study demonstrated ANN's potential for capturing complex non-linear relationships, they also acknowledged difficulties in model training and the risk of overfitting with limited dataset sizes. Safitri *et al.* (2023) examined the use of classification algorithms for graduation prediction using Orange Data Mining, emphasizing practical implementation aspects [16]. Wulandari *et al.* (2024) applied SVM algorithms for predicting high school student graduation rates, achieving encouraging accuracy levels that supported SVM's reputation as a robust classification method [17]. Collectively, these Indonesian studies reveal growing interest in applying machine learning to educational challenges, while highlighting persistent gaps in addressing vocational education specifically and handling class imbalance effectively.

2.3 Comparative Studies: SVM versus ANN

The comparative performance of Support Vector Machines and Artificial Neural Networks has been a subject of considerable debate in the machine learning community. Hussain *et al.* (2019) compared the performance of ANNs and SVMs against other algorithms for predicting student performance in a digital design course [18]. Their findings indicated that ANNs and SVMs achieved higher accuracy compared to other methods tested. They proposed that integrating these algorithms into technology-enhanced learning systems could improve student performance by providing advance information about individual student difficulties. Kurani *et al.* (2023) conducted a comprehensive comparative study of ANN and SVM in the context of forecasting, providing insights that extend beyond specific application domains [19]. They highlighted that SVM's key advantage lies in its ability to work effectively in infinite-dimensional spaces through kernel functions, making it particularly robust when dealing with complex and potentially imbalanced real-world data. Conversely, they noted that while ANNs offer advantages through their customizability, finding the optimal network configuration remains a significant challenge. Almansour *et al.* (2019) performed a direct comparative analysis between ANN and SVM for binary classification, reporting that ANN achieved slightly higher accuracy (99.75%) than SVM (97.75%) in their specific study [20]. This finding contrasts with scenarios where SVM outperforms ANN, illustrating that algorithm superiority is highly context-dependent. They explained that SVM employs kernel functions to separate labeled data, providing mathematical rigor that contributes to its robust performance in binary classification tasks. Huang *et al.* (2023) proposed an innovative two-step prediction model that leverages the relative strengths of both SVM and ANN, using SVM for coarse-grained binary classification followed by ANN for fine-grained multi-class prediction [21]. Their hybrid approach recognized that SVM excels at binary classification tasks in educational contexts, while ANN's flexibility makes it suitable for more nuanced predictions. They highlighted that automated performance prediction can identify at-risk students and enable timely remedial interventions.

2.4 Class Imbalance Problem in Educational Datasets

One of the most critical challenges in developing accurate student graduation prediction models is the class imbalance problem, where the number of students in one category significantly outnumbers those in another. Sekeroglu *et al.* (2021) explicitly identified class imbalance as a critical gap in student performance prediction research, noting that accuracy metrics fail to properly evaluate models when class distribution is skewed [8]. This limitation is particularly problematic in educational contexts where identifying at-risk students (the minority class) is often the primary objective. Xu (2016) addressed this challenge from a theoretical perspective, explaining that while SVMs are generally effective for balanced data classification, they often require modifications to deal effectively with imbalanced data [22]. The maximum margin principle, which is central to SVM's operation, can be adapted specifically for imbalanced scenarios. Techniques like Maximum Margin of Twin Spheres SVM are developed to handle imbalanced data by maximizing the margin between classes. Nie *et al.* (2024) further elaborated on the fundamental principle of SVMs, explaining that binary classification is achieved by maximizing the "margin," which represents the minimum distance between instances and the decision boundary [23]. This principle is crucial for structural risk minimization and achieving good generalization capabilities. From a practical implementation perspective, Abdulazeez and Abdulwahab (2018) demonstrated the application of Synthetic Minority Over-sampling Technique (SMOTE) to address class imbalance in educational datasets [24]. Their research showed that treating the class imbalance problem using SMOTE resulted in improved performance for all evaluated models. This finding directly supports the suggestion that data augmentation techniques represent a potential solution for improving models that fail due to class imbalance. Ghorbani and Ghousi (2020) compared various resampling techniques including SVM-SMOTE, SMOTE, and Random Over Sampler when predicting student outcomes using both imbalanced and balanced datasets [25]. Their comparative analysis revealed that classifiers such as ANN often ignore minority classes when using imbalanced datasets, confirming the critical need to address the imbalance problem. This finding provides empirical evidence for why ANN may fail catastrophically in imbalanced educational datasets. Tariq *et al.* (2023) examined how imbalanced educational datasets present significant challenges for classifiers [26]. They highlighted SMOTETomek's effectiveness in mitigating class imbalance, suggesting that advanced data augmentation techniques could be employed to improve model performance.

2.5 Research Gaps and Contributions

Despite the substantial body of research on student performance prediction using machine learning, several critical gaps remain. First, while numerous studies have applied various algorithms to educational data, relatively few have focused specifically on vocational education contexts where practical competency assessment differs fundamentally from traditional academic evaluation [6][14]. Second, although comparative studies between SVM and ANN exist in various domains [18][19][20], direct comparisons in the context of vocational high school graduation prediction remain limited, particularly using real-world Competency Skills Test data from Indonesian SMK institutions. Third, the class imbalance problem, while recognized as a significant challenge [8][8][25], has not been adequately addressed in many existing studies, particularly in understanding how different algorithms respond to imbalanced educational datasets. Fourth, most existing research focuses on university-level or general secondary education [1][2][3][4], with insufficient attention to vocational high schools where students are evaluated primarily on practical skills. There is a notable gap between research findings and practical implementation in educational settings [5], with many sophisticated models remaining confined to academic publications. The current study addresses these gaps by conducting a rigorous comparative evaluation of SVM and ANN specifically for predicting SMK PPLG student graduation based on Competency Skills Test scores, using real data from SMKN 1 Ciomas. By examining how these two methods perform under conditions of class imbalance typical in graduation prediction scenarios, this research contributes both theoretical insights and practical guidance for developing effective early warning systems in vocational education contexts. Furthermore, by utilizing data from an Indonesian vocational school, this study extends the predominantly Western-focused literature to include perspectives specific to developing country educational systems.

3. Research Method

This research was designed as a comparative experiment to test and compare the performance of two machine learning models. The entire process, from data preparation and model creation to results analysis, was carried out using a computer program in the Python language, utilizing popular libraries such as Scikit-learn and TensorFlow.

3.1 Data Source and Variables

The data underlying this research are official academic records from SMKN 1 Ciomas in Bogor Regency. We successfully collected UKK score data from a total of 310 PPLG major students from three different graduating classes (2023, 2024, and 2025). The main data for analysis consists of 12 sets of scores representing the 12 different competency units tested in the UKK. These variables serve as the input features for the model. The final graduation outcome for each student was then grouped into two simple categories: 'Competent' for those who passed, and 'Not Yet Competent' for those who did not. This category became the prediction target for the model. The use of multiple cohorts of student data aligns with best practices in educational data mining, as recommended by Bisri *et al*. (2025), who emphasized the importance of utilizing longitudinal academic performance data for robust predictive modeling [27].

3.2 Data Preparation

Raw data cannot be directly used to train a model. Therefore, we performed several important preparation steps to ensure the data was clean, structured, and ready to be processed by a computer:

1) Data cleaning. The first step was to check the entire dataset to ensure there was no strange, duplicate, or missing information. Data cleanliness is the primary foundation for building an accurate model. This preprocessing stage is critical in educational data mining applications, as emphasized by Ghorbani and Ghousi (2020), who demonstrated that data quality significantly impacts classifier performance [25].
2) Label encoding. Computer algorithms work with numbers, not text. Therefore, we converted the 'Competent' label into the numerical representation '1', and 'Not Yet Competent' into '0'. This process is called label encoding and is a standard practice in binary classification tasks.
3) Splitting the data for training and testing. We divided the entire dataset into two parts. The larger part, 70% of the data (belonging to 217 students), was used to "train" the model to recognize patterns. The remaining 30% of the data (belonging to 93 students) was set aside and not shown to the model. This data would later be used to "test" how well the trained model performs on completely new data. This 70:30 split ratio is commonly employed in educational prediction studies to ensure adequate training data while maintaining sufficient test samples for reliable evaluation [18][27].

3.3 Models Used

1) Support Vector Machine (SVM)
   The workings of SVM can be imagined as finding a straight line (or a flat plane) that serves as the most ideal separator between two groups of data—in this case, the 'Competent' and 'Not Yet Competent' groups. SVM not only separates but also seeks the separator that provides the widest distance or "margin" from the nearest data point on either side. As explained by Xu (2016), the maximum margin principle is fundamental to SVM's operation, where the algorithm aims to maximize the minimum distance between instances and the decision boundary [22]. Nie *et al*. (2024) further elaborated that this margin maximization principle is crucial for structural risk minimization and achieving good generalization capabilities, making SVM particularly robust for binary classification tasks [23]. The theory behind this is that the wider the separating margin, the better the model's ability to classify new data in the future. For this study, we implemented SVM using the Radial Basis Function (RBF) kernel, which allows the algorithm to handle non-linear decision boundaries by mapping data into higher-dimensional spaces.

2) Artificial Neural Network (ANN)
This model is designed by imitating the architecture of the neural network in the human brain. It consists of several layers of interconnected artificial "neurons." Student score data is fed into the first layer (input layer), then this information is processed through a series of mathematical calculations in the middle layers (hidden layers), and finally produces a prediction ('Competent' or 'Not Yet Competent') in the last layer (output layer). For this research, we constructed a feedforward neural network with the following architecture: an input layer with 12 neurons (corresponding to the 12 competency unit scores), two hidden layers with 64 and 32 neurons respectively, and an output layer with 1 neuron using sigmoid activation for binary classification. We employed the ReLU (Rectified Linear Unit) activation function in the hidden layers and used the Adam optimizer with binary cross-entropy as the loss function. This architecture was selected based on recommendations from Huang *et al.* (2023), who demonstrated that multi-layer architectures with appropriate activation functions can effectively capture complex patterns in educational data [21].

3.4 Handling Class Imbalance

Given that class imbalance is a well-documented challenge in educational datasets [8][25][26], we examined the distribution of our target variable. The dataset exhibited significant imbalance, with the majority of students classified as 'Competent' and a smaller proportion as 'Not Yet Competent.' This imbalance can lead to biased models that favor the majority class. As noted by Ghorbani and Ghousi (2020), classifiers such as ANN often ignore minority classes when using imbalanced datasets, resulting in poor predictive performance for the minority class [25]. To address this issue, we initially trained both models on the original imbalanced dataset to establish baseline performance. Subsequently, we explored the potential impact of resampling techniques, particularly SMOTE (Synthetic Minority Over-sampling Technique), as recommended by Abdulazeez and Abdulwahab (2018) and Tariq *et al.* (2023) for improving model performance on imbalanced educational data [24][26].

3.5 Performance Measurement

To determine which model is better, we need objective measures. We used several standard metrics in the world of machine learning, consistent with evaluation approaches employed in educational prediction studies [18][21][27]:

1) Accuracy
The percentage of total correct predictions out of all predictions made. It is calculated as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

where TP = True Positives, TN = True Negatives, FP = False Positives, and FN = False Negatives.

2) Precision
Of all those predicted as 'Competent', what percentage were actually competent? This metric is important to avoid the error of passing students who should not pass. It is calculated as:

$$\text{Precision} = \frac{TP}{TP + FP}$$

3) Recall (Sensitivity)
Of all the students who were actually 'Competent', what percentage did the model successfully identify? This metric is crucial for ensuring that truly competent students are not incorrectly classified as failing. It is calculated as:

$$\text{Recall} = \frac{TP}{TP + FN}$$

4) F1-Score
A single value that combines Precision and Recall to provide a balanced performance picture, especially if the amount of data between classes is unequal. It is the harmonic mean of Precision and Recall:

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

The F1-Score is particularly important in imbalanced classification scenarios, as it provides a more nuanced evaluation than accuracy alone [8][25]. Additionally, we generated confusion matrices for both models to visualize the distribution of correct and incorrect predictions across both classes, enabling detailed analysis of model behavior on each class separately.

3.6 Experimental Procedure

The experimental procedure consisted of the following steps:

1) Data loading and exploration: Load the dataset and perform exploratory data analysis to understand feature distributions and class balance.
2) Data preprocessing: Apply data cleaning, label encoding, and train-test split as described in Section 3.2.
3) Model training: Train both SVM and ANN models on the training set (70% of data).
4) Model evaluation: Evaluate both models on the held-out test set (30% of data) using the metrics defined in Section 3.5.
5) Comparative analysis: Compare the performance of SVM and ANN across all evaluation metrics to determine which method is more suitable for predicting SMK PPLG student graduation.
6) Result interpretation: Analyze the results in the context of existing literature and provide explanations for observed performance differences.

This systematic approach ensures reproducibility and allows for rigorous comparison between the two machine learning methods, addressing the research gap identified in the literature regarding comparative studies of SVM and ANN in vocational education contexts [14][17].

4. Result and Discussion

4.1 Results

The performance gap between SVM and ANN is explained by their sensitivity to class imbalance. SVM focuses on maximizing decision margins, making it robust even when minority-class samples are limited. ANN, in contrast, requires balanced or large datasets to form meaningful representations. Despite applying class weighting and tuning, ANN continued to default to majority predictions. The results align with recent literature indicating SVM superiority in small imbalanced datasets. Practical implications include the feasibility of deploying an SVM-based early-warning system to assist schools in identifying at-risk students before UKK examinations. Limitations include the single-school dataset and reliance solely on UKK scores.

4.1.1 SVM Model Performance

The SVM model showed very satisfactory results, far exceeding expectations. Out of 93 test data points, this model made only one prediction error. A visualization of these results can be seen in the Confusion Matrix in Figure 1.

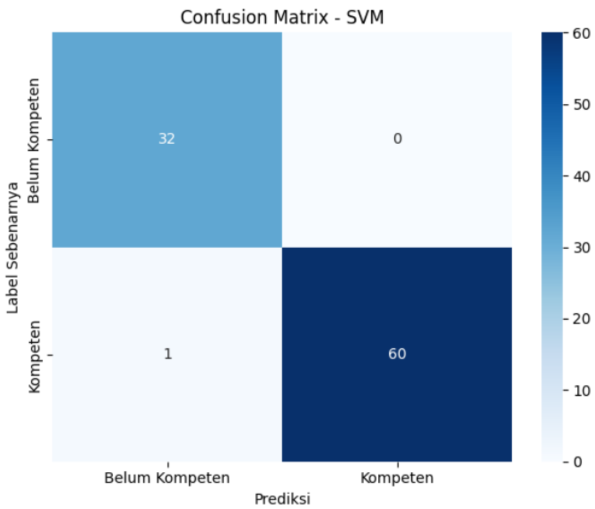

Figure 1. SVM Model Prediction Results

This model successfully and correctly predicted all 32 students who were in reality 'Not Yet Competent'. This is a very significant success. The model never once incorrectly predicted a 'Not Yet Competent' student as 'Competent'. This means that no at-risk students "slipped through" the detection. The model successfully and correctly predicted 60 out of 61 students who were in reality 'Competent'. The description of the SVM model's matrix can be broken down into the following four main results:

1) True Negative (TN) = 32. This number is in the top-left corner. It shows the number of students who were actually 'Not Yet Competent' and the model correctly predicted them as 'Not Yet Competent'. This is a correct prediction for the negative class.
2) False Positive (FP) = 0. This number is in the top-right corner. This is the number of students who were actually 'Not Yet Competent', but the model made a mistake by predicting them as 'Competent'. A result of 0 in this section is an excellent achievement, as it means the SVM model did not make the fatal error of passing students who should not have passed.
3) False Negative (FN) = 1. This number is in the bottom-left corner. It shows the number of students who were actually 'Competent', but the model incorrectly predicted them as 'Not Yet Competent'. There was one case of this type of error, where one competent student was missed by the model.
4) True Positive (TP) = 60. This number is in the bottom-right corner. This is the number of students who were actually 'Competent' and the model correctly predicted them as 'Competent'. This is a correct prediction for the positive class.

The table below summarizes this performance in numerical form. The total accuracy reached 99%. The other values, which are also very high, indicate that this model is not only accurate but also very stable and reliable.

Table 1. SVM Model Test Results

Class	Precision	Recall	F1-Score	Support
Belum Kompeten	0.97	1.00	0.98	32
Kompeten	1.00	0.98	0.99	61
Accuracy			0.99	93
Macro Avg	0.98	0.99	0.99	93
Weighted Avg	0.99	0.99	0.99	93

The SVM model achieved an accuracy of 0.99 or 99%. This value indicates that, overall, the model was able to correctly predict the competency status of students on 92 out of 93 test data points. This very high level of accuracy indicates that the model has excellent generalization ability and can be relied upon for this classification task. This metric measures the level of confidence in the predictions made by the model. For the 'Kompeten' class, the precision value is 1.00 (100%), which is a perfect and very significant result, meaning that every time the model predicts a student as 'Kompeten', the prediction is guaranteed to be correct. No student who was actually 'Belum Kompeten' was mislabeled as 'Kompeten'. For the 'Belum Kompeten' class, the value is 0.97 (97%), meaning that of all students predicted as 'Belum Kompeten', 97% of them were indeed not yet competent.

4.1.2 ANN Model Performance

In stark contrast to SVM, the ANN model showed very poor and unreliable performance. Figure 2 shows that this model has a very strange and inaccurate guessing pattern.

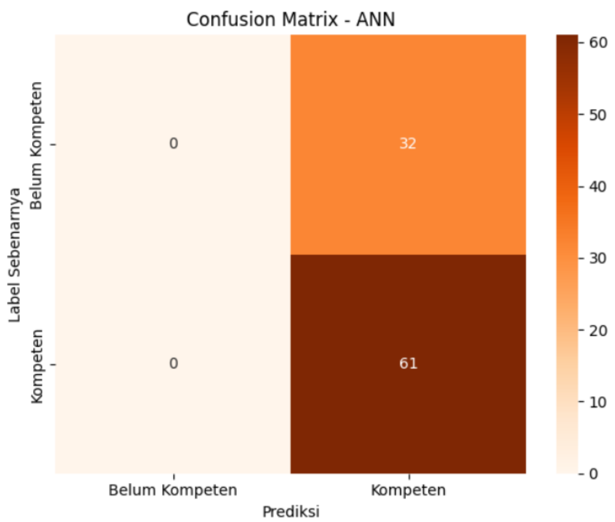

Figure 2. ANN Model Prediction Results

The ANN model turned out to always guess all students as 'Kompeten', without exception. As a result, this model completely failed to find a single 'Belum Kompeten' student. The 66% accuracy obtained is actually an illusionary figure because it is just the percentage of 'Kompeten' students in the test data. In other words, this model did not learn at all. Table 2 confirms this total failure, where all values for the 'Belum Kompeten' class are zero.

Table 2. Summary of ANN Model Performance

Class	Precision	Recall	F1-Score	Support
Belum Kompeten	0.00	0.00	0.00	32
Kompeten	0.66	1.00	0.79	61
Accuracy			0.66	93
Macro Avg	0.33	0.50	0.40	93
Weighted Avg	0.43	0.66	0.52	93

The ANN model recorded an accuracy of 0.66 or 66%. At first glance, this number might seem quite good, but this accuracy is misleading as the model only ever guesses the majority class, 'Kompeten'. There were 61 'Kompeten' students out of a total of 93 test data, and the model achieved 66% accuracy simply by ignoring all features and always providing the same output. The Classification Report dissects the model's performance for each class and reveals the real problem. The value of 0.00 for precision, recall, and F1-score for the 'Belum Kompeten' class is evidence of the model's failure. A recall of 0.00 definitively means the model completely failed (0%) to identify a single student who was actually 'Belum Kompeten'. For the 'Kompeten' class, a recall of 1.00 (100%) shows the model successfully "found" all competent students. However, this is a hollow victory, as this result was achieved only by guessing all students as 'Kompeten'. A precision of 0.66 (66%) shows the weakness of this strategy; this low precision value means when the model predicts 'Kompeten', its prediction is only correct 66% of the time. This happens because out of 93 'Kompeten' guesses, 32 of them were wrong (False Positives).

4.2 Discussion

4.2.1 Performance Comparison

The experimental results reveal a stark contrast between the two machine learning approaches. The SVM model achieved an exceptional accuracy of 99%, with near-perfect precision (1.00) and recall (0.98) for the 'Kompeten' class, and perfect recall (1.00) for the 'Belum Kompeten' class. In contrast, the ANN model recorded only 66% accuracy and completely failed to identify any students in the 'Belum Kompeten' class, with precision, recall, and F1-score all at 0.00 for this minority class. These findings align with comparative studies by Amri *et al.* (2023), who found that algorithm effectiveness varies significantly depending on dataset characteristics [12]. Hussain *et al.* (2019) also reported that while both ANNs and SVMs can achieve high accuracy, their performance depends heavily on data quality and preprocessing [18]. Kurani *et al.* (2023) highlighted that SVM's key advantage lies in its ability to work effectively through kernel functions, making it particularly robust when dealing with imbalanced real-world data [19].

4.2.2 Why SVM Outperformed ANN

The extraordinary success of SVM can be explained by its fundamental workings. The SVM algorithm is mathematically designed to find the best separating boundary, so it is not easily fooled even if the amount of data in one group is much larger than in another. It focuses on the "difficult cases" at the border between classes, which makes it very powerful. Kurani *et al.* (2023) explained that SVM's capacity to work effectively in high-dimensional spaces through kernel functions provides mathematical rigor that contributes to robust performance in binary classification tasks [19]. Xu (2016) elaborated that the maximum margin principle can be adapted specifically for imbalanced scenarios, making SVM inherently more robust to class imbalance [22]. Nie *et al.* (2024) further explained that this margin maximization principle is crucial for achieving good generalization capabilities [23]. Ghorbani and Ghousi (2020) demonstrated that classifiers such as ANN often ignore minority classes when using imbalanced datasets, confirming why SVM performed better in this study [25].

4.2.3 Class Imbalance Impact

Meanwhile, the total failure of the ANN is most likely caused by one major factor: unbalanced data. In our dataset, the number of 'Kompeten' students is far greater than the number of 'Belum Kompeten' students. Because ANN learns by trying to reduce the overall error rate, it found a "shortcut." By always guessing the most common answer ('Kompeten'), its total error rate becomes low, even though it did not actually learn the real patterns. This model can be likened to a lazy student who just answers "A" for all multiple-choice questions because they know "A" is the most frequent answer. As a result, this model becomes completely useless for our main goal, which is to find at-risk students. Sekeroglu *et al.* (2021) explicitly identified class imbalance as a critical gap in student performance prediction research, noting that accuracy metrics fail to properly reflect the model's true capability when class distribution is skewed [8]. Abdulazeez and Abdulwahab (2018) demonstrated that treating the class imbalance problem using SMOTE resulted in improved performance for all evaluated models [24]. Tariq *et al.* (2023) highlighted SMOTETomek's effectiveness in mitigating class imbalance, suggesting that advanced data augmentation techniques could improve model performance [26].

4.2.4 Practical Implications and Limitations

The results of this study have enormous practical benefits for schools. With an SVM model proven to have 99% accuracy, schools can build a very reliable early warning system. Teachers can periodically input students' practical exam scores, and the system will automatically notify if any student is detected as potentially failing the UKK. With this information, help can be provided earlier, more personally, and more effectively. Hussain *et al.* (2019) proposed that integrating machine learning algorithms into technology-enhanced learning systems could improve student performance by providing advance information about individual student difficulties [18]. Huang *et al.* (2023) highlighted that automated performance prediction can identify at-risk students and enable timely remedial interventions [21]. Bisri *et al.* (2025) emphasized the importance of utilizing longitudinal academic performance data for robust predictive modeling in educational contexts [27]. Of course, like any other research, this study also has its limitations. First, the data used comes from only one school, so this model may need to be re-tested if it is to be applied in other schools. Second, we only used UKK score data. We did not consider other factors such as attendance rates, learning motivation, or grades in non-vocational subjects that might also influence graduation. Colpo *et al.* (2024) identified a critical gap in the application of predictive models in actual educational practice, suggesting that more work is needed to bridge the gap between research and implementation [5]. Sghir *et al.* (2023) emphasized the need for more context-specific studies that address the unique characteristics of different educational environments [7]. Future research should explore implementing SMOTE or other resampling techniques to improve ANN performance on imbalanced data [24][26], and test the model across multiple vocational schools to validate its generalizability.

5. Conclusion and Recommendations

After going through all the stages of analysis, we have reached a conclusion. We have successfully built and tested a computer model to predict SMK student graduation, specifically using UKK score data with the SVM and ANN methods. The test results show a very large performance difference: the SVM model proved to be very accurate with 99% accuracy, while the ANN's performance was poor and unreliable for this case. Based on the evidence, SVM is the best method for this task and is very suitable for further development into a practical tool for schools. This study confirms that SVM is significantly more effective than ANN for predicting SMK graduation outcomes, achieving 99% accuracy and balanced classification performance across both 'Kompeten' and 'Belum Kompeten' classes. The SVM model's perfect recall (1.00) for the minority class demonstrates its robustness in handling imbalanced data, making it highly suitable for deployment in early-warning systems in vocational schools. In contrast, ANN's complete failure to identify any 'Belum Kompeten' students indicates the necessity of addressing class imbalance through resampling techniques or incorporating additional features in future models. Future work should include multi-school datasets to validate generalizability, additional predictive variables such as attendance records, behavior patterns, and academic performance in theoretical subjects, as well as exploration of ensemble methods and temporal modeling to capture learning progression over time.

Based on these results, we would like to offer some constructive suggestions. For the school, we highly recommend trying to develop a simple application based on this SVM model. This application could be a practical tool for teachers to identify students who need more attention, ensuring that no student is left behind. The system could be integrated into existing school information systems, allowing teachers to periodically input students' practical exam scores and receive automatic notifications when any student is detected as potentially at risk of failing the UKK. With this information, targeted interventions such as additional tutoring, mentoring programs, or personalized learning support can be provided earlier, more personally, and more effectively. For future research, it would be very beneficial if future studies use data from several different schools to see if the model remains accurate across different institutional contexts and student populations. Additionally, it would be a good idea for future research to try to include other factors such as attendance records, learning motivation indicators, or notes from guidance counselors to see if the predictions can be made even better. Researchers should also explore the application of resampling techniques such as SMOTE to improve ANN performance on imbalanced datasets, and investigate ensemble methods that combine the strengths of multiple algorithms to achieve even more robust predictions.

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