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Early Detection of Mental Health Risk Indicators in Children Using Machine Learning Based on Teacher Questionnaires in Islamic Early Childhood Education in Gorontalo.

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Abstract

This study aims to identify indicators of mental health risk in early childhood through the development of a machine learning-based system and to analyze its implications for education. Mental health in early childhood is a crucial aspect that supports optimal development. Various internal and external factors influence the development of children's mental health. Early detection of risk indicators enables appropriate interventions to prevent more serious problems in the future. This research utilizes data collected from 100 randomly selected PIAUD (Islamic Early Childhood Education) teachers in Gorontalo Province. The K-Means Clustering algorithm is used to group the data and form target variables, while the Decision Tree algorithm is employed for classification. The results show that the Decision Tree model achieves an accuracy of 85% in predicting mental health risks in children. Indicators such as "Withdrawal," "Easily Angered," "Weight Change," and "Eating Problems" are identified as key factors. This prediction system is expected to serve as a helpful tool for teachers and parents in conducting early detection and providing appropriate interventions.

Keywords: *Early Childhood; Early Detection; Decision Tree; Mental Health; Machine Learning*

Deteksi Dini Indikator Resiko Kesehatan Mental pada anak Menggunakan Machine Learning Berbasis Kuesioner Guru pada pendidikan Islam Anak Usia Dini di Gorontalo

Abstrak

Penelitian ini bertujuan mengidentifikasi indikator risiko kesehatan mental pada anak usia dini melalui pengembangan machine learning dan menganalisis implikasinya bagi pendidikan. Kesehatan mental anak usia dini merupakan aspek krusial yang menunjang perkembangan optimal. Beberapa faktor internal dan eksternal, mempengaruhi perkembangan kesehatan mental anak. Deteksi dini indikator risiko memungkinkan intervensi yang tepat untuk mencegah permasalahan yang lebih serius. Penelitian ini memanfaatkan data dikumpulkan dari 100 guru PIAUD (Pendidikan Islam Anak Usia Dini) di Provinsi Gorontalo yang dipilih secara acak. Algoritma K-Means Clustering digunakan untuk mengelompokkan data dan membentuk variabel target, sedangkan algoritma Decision Tree digunakan untuk klasifikasi. Hasil penelitian menunjukkan bahwa model Decision Tree mencapai akurasi sebesar 85% dalam memprediksi risiko kesehatan mental pada anak. Indikator "Menarik Diri", "Mudah Marah", "Perubahan Berat Badan", dan "Masalah Makan" teridentifikasi sebagai faktor penting. Sistem prediksi ini diharapkan dapat menjadi alat bantu bagi guru dan orangtua dalam melakukan deteksi dini dan intervensi yang tepat.

Kata kunci: *anak usia dini; deteksi dini; Decision Tree; kesehatan mental; Machine learning.*

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A. Introduction

The development of early childhood is a crucial period as the foundation for holistic growth [1] and individual development[2]. In the age range of 0 to 8 years, children experience development in various aspects including physical, cognitive, language,[3] socio-emotional, and moral moral[4]. Each aspect of development is interconnected and forms the basis for personality, learning abilities, and the well-being of children in the future. In terms of development, mental health in early childhood plays a vital role in ensuring optimal development. Children with good mental health are able to express emotions appropriately, build positive social relationships, develop self-confidence, and demonstrate resilience in facing challenges and pressures. Issues regarding mental health in early childhood have become fundamental concerns [5].

Data from the World Health Organization (WHO) in 2020 indicates that mental disorders among children and adolescents are an increasingly urgent health issue. WHO reported that 1 in 7 children and adolescents aged 10 to 19 years experience mental disorders, which amounts to 13% of the total global disease burden in this age group [6]. Epidemiological studies show that the most common disorders among children and adolescents are depression, anxiety, and

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behavioral disorders [7]. These disorders can significantly impact their social [8] and emotional development [9].

The first national mental health survey in Indonesia, the National Adolescent Mental Health Survey (I-NAMHS), which measures the incidence of mental disorders among adolescents aged 10 – 17 years in Indonesia, shows that one in three Indonesian adolescents has mental health issues. This data underscores the importance of promotive and preventive efforts in maintaining early childhood mental health, [10] including early detection and appropriate interventions[11].

There are several risk factors that affect early childhood mental health. These factors include biological factors, such as genetics and family health history; environmental factors, such as parenting styles, family dynamics, and exposure to trauma; and social factors, such as economic status, discrimination, and access to health services [12]. One risk factor that has a significant impact on children's mental health is the experience of violence. Violence, whether physical, emotional, or

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sexual, can lead to profound psychological trauma and increase children's vulnerability to various mental disorders [13].

Studies show that children who are victims of violence have a higher risk of experiencing depression, anxiety, post-traumatic stress disorder (PTSD), and behavioral problems [14] [15]. Experiences of violence can disrupt brain development, affect emotion regulation capabilities, and create negative social interaction patterns [16] [17]. Furthermore, longitudinal research reveals that Adverse Childhood Experiences (ACEs), including violence, neglect, and family dysfunction, are associated with an increased risk of physical and mental health problems in adulthood. These findings emphasize the urgency of protecting children from violence and providing comprehensive support for children who have been victims of violence [18].

Early childhood mental health is a vital foundation for optimal emotional, social, and cognitive development. At this early stage, various psychological and behavioral aspects begin to form, so any disturbances that arise during this period can have long-term impacts on a child's life. Therefore, early detection of potential mental health risk is crucial, especially in the context of early childhood education, including within Islamic Early Childhood Education institutions (PIAUD).

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In the context of Islamic Early Childhood Education (PIAUD), attention to children's mental health is an integral part of the holistic educational goals, which aim to shape well-rounded individuals spiritually, emotionally, and socially from an early age. PIAUD not only instills Islamic values but also creates a loving, safe, and supportive learning environment that nurtures children's mental development. Through value-rich learning activities and child-friendly approaches, PIAUD teachers hold a strategic position in observing early signs of behavioral or emotional disorders. Therefore, it is essential for PIAUD institutions to focus not only on cognitive and spiritual aspects but also to be proactive in identifying indicators of mental health risks in children as part of a comprehensive and sustainable educational effort.

Early childhood educators become the frontline in the early detection of mental health risk indicators in early childhood. becomes the frontline in the early detection of mental health risk indicators in early childhood. They have intensive interactions with children and have time to observe children's behaviors, emotions, and social interactions directly. This emphasizes the important role of teachers in identifying the early signs of mental health issues in children, such as changes in behavior, learning difficulties, or emotional disturbances. However, this early identification process often faces challenges, including a lack of teachers' knowledge about children's mental health, limitations of comprehensive screening tools, and the stigma still attached to mental health issues.

The development of machine learning technology offers innovative solutions to enhance the accuracy and efficiency of early detection of mental health problems in early childhood. Machine learning is a branch of artificial intelligence that enables computers to learn from data and identify patterns without being explicitly programmed [19]. In the context of mental health, machine learning can be utilized to analyze children's behavioral data, such as that obtained from teacher

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questionnaires, and identify children who are at risk of experiencing mental health issues. The ability of machine learning to process complex data and detect patterns that are difficult to recognize manually makes it a valuable tool in supporting early detection efforts [20].

Several studies have applied machine learning to detect mental disorders in the adult population [21]. By using machine learning algorithms to predict the risk of postpartum depression in pregnant women. This study shows that machine learning is capable of identifying at-risk individuals with high accuracy [22]. However, the application of machine learning in the early detection of mental health issues in young children, particularly through the analysis of data from teacher questionnaires, is still limited.

Therefore, this study aims to develop a machine learning-based prediction system that can early detect indicators of mental health risk in young children by utilizing teacher questionnaire data. The data used in this research comes from questionnaires filled out by 100 early childhood education teachers in Gorontalo Province. This questionnaire contains questions related to various indicators of mental health risk in children, as listed in the dataset "predataset.csv". The novelty of this research lies in the application of machine learning for the early detection of mental health issues in young children in Indonesia, using teacher questionnaire data as the primary source of information.

This research is expected to contribute to efforts in the early detection and intervention of mental health issues in children, thereby improving children's well-being and preventing negative impacts in the future. The developed prediction system is expected to serve as a tool for teachers, parents, and professionals in the field of early childhood education to identify children at risk of mental health

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issues more early, accurately, and efficiently. Thus, appropriate interventions can be provided promptly to support optimal child development.

B. Research Methods

The research methodology is designed to systematically and accurately answer research questions. A quantitative approach was chosen because this research focuses on the analysis of numerical data obtained from questionnaires to identify patterns and relationships between variables related to mental health risk indicators in young children. A cross-sectional design is used because data is collected at a specific point in time, providing an overview of the mental health condition of young children in Gorontalo Province based on the perspective of early childhood education teachers at the time the research is conducted.

Sample selection was done randomly to ensure a good representation of the population of early childhood education teachers in Gorontalo Province. A total of 100 early childhood education teachers from various institutions and backgrounds were selected as research participants. Simple random sampling techniques were applied to ensure that each early childhood education teacher in the province had an equal opportunity to be selected as a sample. This is important to minimize bias and enhance the generalization of research results.

Data collection was carried out using a questionnaire that has been tested for validity and reliability. The instrument validation process involved assessment by experts in the field of early childhood education and children's mental health. The reliability of the instrument was tested using Cronbach's alpha technique > 70 to measure the internal consistency of the instrument. This questionnaire contains questions that measure various mental health risk indicators in young children, such as irritability, withdrawal, sleep disturbances, risky behavior, isolation, weight changes, eating problems, anxiety, sadness, difficulty expressing oneself, self-harm, difficulty following rules and social norms, and aggressive behavior or bullying towards peers. Examples of questions in the questionnaire include:

"How often does the child appear irritable, offended, or frustrated?"

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"Does the child show withdrawal behavior and refuse to interact with others?"

"Does the child have difficulty sleeping or experience nightmares?"

Teachers are asked to answer these questions based on their observations and assessments of their students' behavior. A Likert scale is used to measure the intensity or frequency of each risk indicator. The collected data is then processed and analyzed using machine learning techniques. The data analysis stages are carried out systematically using the Python programming language and several supporting libraries, such as Pandas for data manipulation, Scikit-learn for the implementation of machine learning algorithms, and Matplotlib for data visualization. Here is a further explanation of the data analysis stages.

Starting from the initial stage, Data Preparation. This stage includes data cleaning, data transformation, and feature engineering. Data cleaning is performed to handle missing values or invalid data. Data transformation is done to adjust the scale of the data or change the data format to meet the requirements of the machine learning algorithms. Feature engineering is performed to create new features that are more informative than the existing features. In the second stage, the formation of the Target Variable. The K-Means Clustering algorithm is used to group the data into 2 clusters based on patterns in the questionnaire data. The optimal number of clusters is determined using the Elbow method. This method helps find the most appropriate number of clusters by analyzing the variation of inertia (the sum of square distances between data points and cluster centers) against the number of clusters. The cluster with the highest average risk indicator value is labeled "At Risk," while the cluster with the lowest average risk indicator value is labeled "Not At Risk." These cluster labels are then used as the target variable "Mental Health Risk" to train the classification model. In the third stage, the training process of the classification model. The Decision Tree algorithm is chosen for its ability to generate models that are easy to interpret and individualize. The data is divided into training data (80%) and testing data (20%) using stratified random sampling techniques to ensure balanced class proportions (At Risk/Not At Risk) in both datasets.

The Decision Tree model is then trained using the training data and the model parameters are optimized to achieve the best performance. The fifth stage involves evaluating the Model Performance, where the performance of the Decision Tree model is evaluated using the testing data. The evaluation metrics used include measuring the accuracy of the proportion of correct predictions from all predictions, measuring the precision of the proportion of true positive predictions from all positive predictions, the Recall process which measures the proportion of true positive predictions from all actual positive data, and finally the F1-score, which is the harmonic mean between precision and recall. The fifth stage is Interpretation and Visualization. At this stage, the trained Decision Tree model is then individualized in the form of a decision tree. This visualization facilitates model interpretation and identification of important factors influencing mental health risks in children. In addition, feature importance is also analyzed to determine the extent of each feature's contribution to the model's predictions.

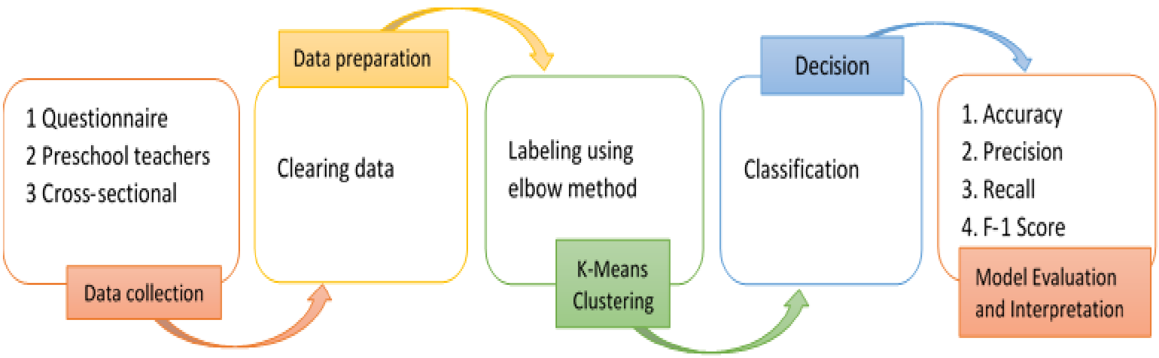

Figure 1. Stages of research on Early Detection of Mental Health Risk Indicators in Early Childhood through the Utilization of Machine Learning and Its Implications for Education

C. Results and Discussion (Cambria, Bold, Size 12, 1,5 Space)

1. *Optimization Analysis of Cluster Numbe*

Before classification with the Decision Tree is performed, the data is first grouped into 2 clusters using the K-Means Clustering algorithm. The optimal number of clusters is determined using the Elbow Method as clearly shown in Figure 1, which presents the Elbow Method graph used to determine the optimal number of clusters in the K-Means Clustering algorithm. The X-axis on the graph

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indicates the number of clusters (K), while the Y-axis shows the inertia value. Inertia is the sum of the squared distances between data points and the centroid of their cluster. The smaller the inertia value, the better the data clustering. In the Elbow Method graph, we look for the "elbow" point or the point where the decrease in inertia value begins to slow down. This point indicates the optimal number of clusters. In Figure 1, the elbow point is at K = 3, so 3 clusters are chosen for this analysis. Choosing the right number of clusters is very

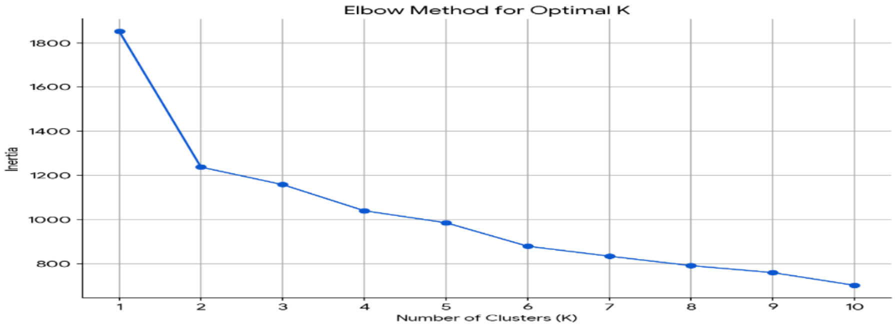

Figure 2. Grafik Elbow Method

After the data was clustered into 3 clusters using the K-Means Clustering algorithm, the characteristics of each cluster were analyzed further. The following tables present the average values of each mental health risk indicator for each cluster. This analysis aims to understand the mental health risk profile of each group of children that has been formed. Table 1 presents the average values of each mental health risk indicator for children included in the At-Risk cluster. These average values provide an overview of the behavioral trends and emotional conditions of children who are at high risk of experiencing mental health issues.

Table 1. Average Indicator Value of Mental Health Risk in At-Risk Clusters

Mental Health Risk Indicators	**Average Value**
Irritable	2.615
Withdraw	4.308
Sleep Disorder	2.615
Academic decline	3.538
Risky Behavior	2.923
Alone	3.462
Weight Change	2.846
Eating Problems	3.231
Anxious	3.000
Sad	2.923

Table 1 shows the profile of children identified as being at high risk of experiencing mental health issues. It can be seen that the average scores on all risk indicators are relatively high, indicating a strong signal regarding their mental health condition. Some prominent indicators include "Withdrawing" (4.308), "Easily Angry" (2.615), and "Difficulty Expressing" (3.846). The interpretation of Table 1 is very clear: for the Withdrawing indicator (4.308), children in this cluster tend to exhibit behavior of withdrawing from social interactions, preferring to be alone, and avoiding contact with others. This may indicate the presence of social anxiety, depression, or other disorders that make it difficult for them to socialize with their peers. The Easily Angry indicator (2.615), children in this cluster tend to be more easily angered, offended, or frustrated. They may show excessive emotional reactions to situations that others consider trivial. This may indicate issues with emotional regulation or other behavioral disorders. The Difficulty Expressing indicator (3.846), children in this cluster have difficulty expressing their emotions both verbally and non-verbally. They may struggle to articulate their feelings, whether positive or negative. This may indicate communication disorders or emotional disorders that make it hard for them to communicate effectively.

Furthermore, Table 2 displays the average scores of mental health risk indicators in children who are part of the Moderate cluster. The profile of children in this cluster shows several indicators that need attention, although overall their risk is lower compared to the High-Risk cluster.

Table 2. Average Value of Mental Health Risk Indicators in the Medium Cluster

Mental Health Risk Indicators	**Average Value**
Irritable	3.474
Withdraw	2.474
Sleep Disorder	2.421
Academic decline	3.211
Risky Behavior	1.789
Alone	2.895

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Weight Change	3.421
Eating Problems	3.211
Anxious	2.211
Sad	2.158
Difficult Expressions	2.368
Self-harm	1.895
Difficult Rules	2.579
Aggressive	2.632

This table shows the profile of children at moderate risk of experiencing mental health issues. The average indicator values in this cluster are lower compared to the "At Risk" cluster, but there are still several indicators that need attention, such as "Irritable" (3.474), "Weight Changes" (3.421), and "Eating Problems" (3.211).

Interpretation:

- **Irritable (3.474):** Although not as high as the "Risky" cluster, children in this cluster also tend to display quite intense feelings of anger. They may be more sensitive to criticism or rejection and easily frustrated when facing difficulties.
- **Weight Changes (3.421):** Children in this cluster experience significant weight changes, both loss and gain. Drastic weight changes can indicate underlying physical or mental health issues, such as eating disorders or depression.
- **Eating Problems (3.211):** Children in this cluster show issues in their eating patterns, such as a drastically decreased or increased appetite, being picky about food, or refusing to eat. Eating problems can indicate the presence of eating disorders, digestive issues, or emotional disturbances affecting their appetite.

a) Indicator of Mental Health Risk for the Non-Risk Cluster and Its Interpretation

Finally, Table 3 presents the average values of mental health risk indicators for children in the Non-Risk cluster. This profile provides an overview of the characteristics of children who tend to have good mental health conditions.

Table 3. Average Mental Health Risk Indicator Score in the Non-Risk Cluster

Mental Health Risk Indicators	Average Value
Irritable	2.088
Withdraw	1.765
Sleep Disorder	1.471
Academic decline	1.779
Risky Behavior	1.044
Alone	1.529
Weight Change	1.368
Eating Problems	1.662
Anxious	1.279
Sad	1.147
Difficult Expressions	1.471
Self-harm	1.015
Difficult Rules	1.162
Aggressive	1.088

The table shows the profile of children identified as having a low risk of experiencing mental health problems. The average scores on all risk indicators are relatively low, indicating that children in this cluster tend to have good mental health. Interpretation Children in this cluster generally exhibit healthy and adaptive behaviors and emotions. They are able to regulate their emotions well, interact positively with others, and adjust to their environment. Nevertheless, it is important to remember that each child is unique and may experience changes in their development. Therefore, ongoing observation and assessment are still necessary to ensure that each child receives the appropriate support according to their needs.

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Analysis Classification Results

After the target variable is formed, the Decision Tree model is trained to classify the data and predict mental health risks. Figure 2 shows the visualization of the resulting Decision Tree.

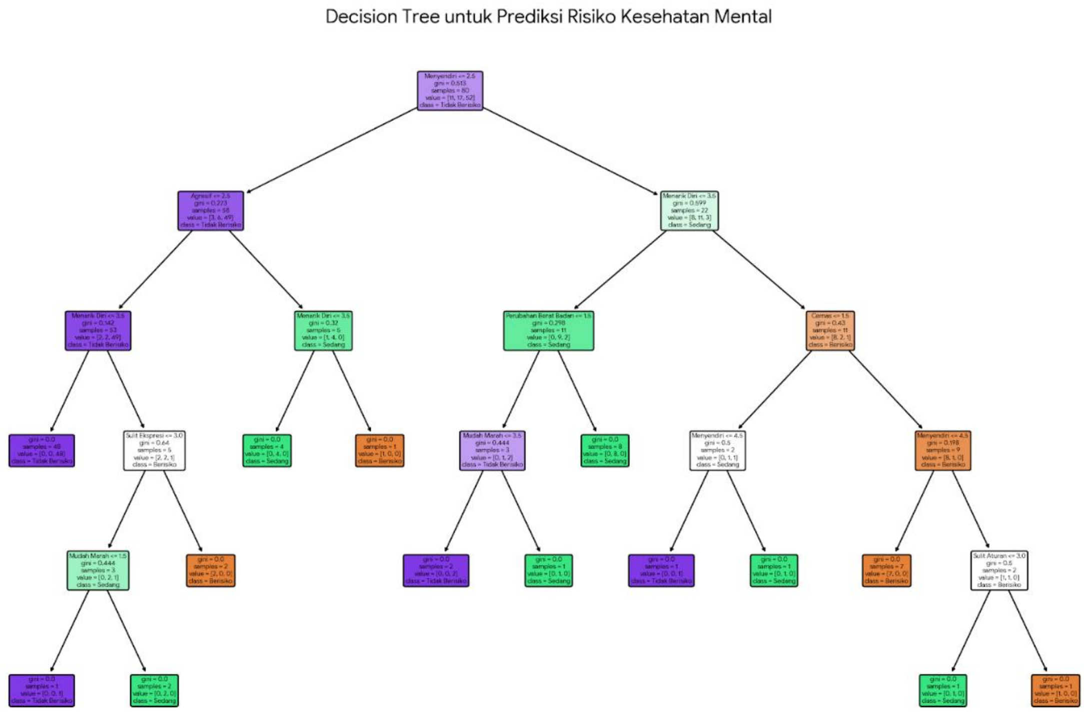

Figure 3. Visualisasi *Decision Tree*

The generated Decision Tree has a depth of 5 and consists of 11 nodes. The root node uses the indicator "Withdrawal" as the criterion for data splitting. If the value of "Withdrawal" is greater than 2.5, then the data will be classified into the right branch. Conversely, if the value of "Withdrawal" is less than or equal to 2.5, then the data will be classified into the left branch. This process continues until reaching a leaf node that indicates the predicted class (At Risk/Not At Risk).

This Decision Tree shows that the indicator "Withdrawal" is the most important factor in determining mental health risk in children. Other indicators that are also important include "Easily Frustrated," "Weight Change," and "Eating Problems." Model evaluation of the Decision Tree on the test data shows fairly good results, as shown in Table 4.

Table 4. Evaluation of the Decision Tree model on the test data

Model	Accuracy	Precision	Recall	F1-score
Decision Tree	0.85	0.88	0.85	862.581

The Decision Tree model achieved an accuracy of 85%, which means the model was able to correctly predict 85% of the test data. The precision value of 88% indicates that of all the data predicted to be positive (At Risk), 88% of them are actually positive. *The recall* value of 85% indicates that the model was able to identify 85% of all data that was actually positive. The F1-score of 0.86 is the harmonic mean between precision and *recall*, indicating a balance between the two metrics.

Discussion

The results of this study show that the K-Means Clustering and Decision Tree algorithms can be applied to early detection of mental health risk indicators in early childhood based on teacher questionnaire data. The resulting Decision Tree model shows good accuracy in predicting mental health risks in children.

Some of the indicators identified as important factors in determining mental health risk were "Withdrawal", "Irritability", "Weight Change", and "Eating Problems". This finding is in line with previous research which shows that behavioral changes, such as social withdrawal, increased negative emotions, and eating disorders, are early signs of mental health problems in children. The "Withdrawal" indicator, which is an important factor in the Decision Tree model, shows that changes in children's social interactions are one of the crucial signals that teachers and parents need to pay attention to. Children experiencing mental health problems tend to exhibit withdrawn behavior, avoid social contact, and confine themselves. These behaviors can be indicative of emotional difficulties, anxiety or depression. Child abuse, whether physical, emotional or sexual, can be one of the triggers for mental health problems in early childhood. Further studies show that abused children have a higher risk of developing depression, anxiety and behavioral disorders. Violence can cause deep psychological trauma to children, disrupting their brain development. The Decision Tree can be interpreted as follows:

1) Root node

The root node uses the "Withdrawal" indicator as the data sharing criteria. If the "Withdraw" value is more than 2.5 (Likert scale 1-5), then the child is indicated to have a higher mental health risk and the data will be classified to the right branch. Conversely, if the "Withdraw" value is less than or equal to 2.5, then the child is indicated to have a lower risk and the data will be classified to the left branch.

2) Right branch

On the right branch, the next division criterion is the "Alone" indicator. If the "Alone" value is more than 3.5, then the child is classified as "At Risk". However, if the "Alone" value is less than or equal to 3.5, then the next criterion used is "Aggressive". If the "Aggressive" value is more than 1.5, then the child is classified as "At Risk", and if it is less than or equal to 1.5, then it is classified as "Moderate".

Analisis *Feature Importance*

Selain menganalisis struktur *Decision Tree*, *feature importance* juga dianalisis untuk mengetahui seberapa besar kontribusi masing-masing fitur dalam prediksi model. Tabel 5 menunjukkan nilai *feature importance* dari masing-masing fitur.

Table 5. Average Mental Health Risk Indicator Scores in the Not at Risk Cluster

Features	Value
Alone	337.027
Withdraw	270.943
Aggressive	162.639
Irritable	649.219
Anxious	474.618
Weight Change	472.159
Difficult Expressions	454.453
Difficult Rules	243.457

Sleep Disorder	0
Academic decline	0
Risky Behavior	0
Eating Problems	0
Sad	0
Self-harm	0

From Table 5, it can be seen that "Aloof" is the most important feature in the *Decision Tree* model, followed by "Withdrawn" and "Aggressive". Other features have relatively low *feature importance* values.

The results of this study are in line with several previous studies showing that changes in behavior and emotions are important indicators of mental health problems in early childhood. For example, some studies have found that children with anxiety disorders often exhibit avoidant behavior, fear separation from parents, and have difficulty sleeping. Other studies have shown that children with depression tend to show sad facial expressions, lose interest in previously favored activities, and experience changes in appetite and sleep patterns. The findings of this study have important implications for early detection and intervention of mental health problems in early childhood. ECD teachers, as individuals who interact intensively with children, have a crucial role in identifying early signs of mental health problems. By understanding the risk indicators identified in this study, teachers can conduct more targeted observations and assessments to detect children at risk of mental health problems.

It is important to remember that the *machine learning* model developed in this study is only a tool for early detection. Diagnosis and treatment of mental health problems should still be done by professionals, such as psychologists or psychiatrists. Therefore, if teachers find indications of mental health problems in children, they should immediately consult with professionals for proper assessment and intervention.

This research also provides new insights into the application of *machine learning* in the field of early childhood education. The development of a *machine*

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learning-based prediction system can help teachers and parents to conduct early detection of mental health problems in children more accurately and efficiently. This can increase the effectiveness of early intervention and prevent greater negative impacts in the future. Nonetheless, this study has some limitations. First, the data used only came from one source, the teacher questionnaire. Data from other sources, such as direct observation or interviews with parents, could strengthen the validity of the results. Second, the sample size used was relatively small (100 respondents). Research with a larger sample size is needed to improve the generalizability of the research results. Third, the *machine learning* model developed in this study needs to be further tested and validated in a wider population to ensure its effectiveness.

Conclusion

This research successfully developed a machine learning-based prediction system for early detection of mental health risk indicators in early childhood by utilizing teacher questionnaire data. The resulting Decision Tree model shows good performance with accuracy reaching 85%. K-Means Clustering analysis grouped the data into three clusters, namely "At Risk", "Moderate", and "Not at Risk", with different characteristics on mental health risk indicators. Decision Tree identified "Withdrawal", "Irritability", "Weight Change", and "Eating Problems" as important indicators that need attention.

This prediction system is expected to be a tool for teachers, parents and professionals in identifying children at risk of mental health problems, so that appropriate interventions can be provided immediately and prevent greater negative impacts.

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