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Research Paper

Analysis of classification algorithms for Machine Learning using the SPSS Method

Didit Suprihanto [1], Retantyo Wardoyo[2]

[1] *Department of Electrical Engineering,Universitas Mulawarman, Kalimantan Timur, Indonesia*
[2] *Department of Computer Sciences & Electronics,Universitas Gadjah Mada Sekip Utara, Bulaksumur, Yogyakarta 55281 Indonesia*

e-mail: didit.suprihanto@ft.unmul.ac.id, rw@ugm.ac.id

**Corresponding Author: didit.suprihanto@ft.unmul.ac.id*

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Abstract: *Machine learning, a cornerstone of computer science and artificial intelligence, encompasses the use of algorithms to replicate human learning processes and enhance accuracy. Coined by Arthur Samuel in 1959, it signifies the field where algorithms acquire learning capabilities without explicit programming, liberating machines to learn from their experiences—a hallmark of computational intelligence. Its wide-ranging applications are evident in recommender systems, such as Netflix's movie and TV show recommendations, which amalgamate collaborative and content-based filtering. Reinforcement learning further elevates recommendation systems by enabling agents to adapt suggestions based on user interactions, like tracking viewing habits. The research in machine learning holds paramount importance due to its transformative influence across various domains. It optimizes efficiency by automating intricate processes, streamlining decision-making, and expediting operations in industries spanning healthcare, finance, transportation, and manufacturing through data analysis and pattern recognition. Moreover, machine learning facilitates predictive modeling, enhancing forecasting accuracy for weather, investments, and medical diagnoses, thus aiding in informed decision-making and risk management. The abstract also briefly touches upon IBM's SPSS statistics software, a multifaceted tool for advanced analytics and data management, and alludes to Cronbach's Alpha as a reliability measure. With an overall Cronbach's Alpha value of .572, the abstract suggests its model is suitable for analysis, aligning with the literature review's findings.*

Keywords: *Machine learning, Recommender systems, Reinforcement learning, Efficiency, Predictive modeling*

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1. Introduction

Machine Learning, a transformative field at the intersection of computer science and artificial intelligence (AI), has irrevocably reshaped the way we approach complex problems, automate decision-making, and glean insights from data. At its essence, Machine Learning empowers systems to learn patterns, recognize trends, and make predictions autonomously, all without the need for explicit programming. In this comprehensive introduction, we embark on a journey to explore the foundational principles, historical milestones, diverse techniques, and wide-ranging applications that define the landscape of Machine Learning.

1.1. Historical Foundations

The roots of Machine Learning trace back to a quest to bestow machines with the remarkable ability to learn from data and improve their performance over time, mirroring human cognitive processes. The seminal term "Machine Learning" was first coined by Arthur Samuel in 1959, reflecting a pivotal moment in the field's evolution. Samuel's pioneering work in creating a checkers-playing program that honed its skills through iterative gameplay laid the cornerstone for the future of AI and Machine Learning.

The trajectory of Machine Learning has witnessed several distinct eras:

Early Foundations: In its infancy, Machine Learning primarily revolved around symbolic AI and rule-based systems, exemplified by expert systems designed to encode human knowledge into logical rules. While these systems demonstrated the potential for knowledge representation and reasoning, they exhibited limitations in adaptability and generalization.

Connectionism and Neural Networks: The 1980s witnessed a resurgence of interest in neural networks and connectionist models, inspired by the architecture of biological neural systems. This era laid the groundwork for Deep Learning, characterized by the use of multi-layered artificial neural networks for tasks such as pattern recognition.

Statistical Learning: Concurrently, the Machine Learning landscape was enriched by statistical learning approaches, emphasizing the significance of probabilistic models and mathematical techniques in data analysis. Decision trees, Bayesian networks, and support vector machines emerged as powerful tools for classification and regression tasks.

Big Data and Deep Learning: The 21st century ushered in a new era fueled by the exponential growth of data, computational resources, and algorithmic innovations. Deep Learning, marked by the utilization of deep neural networks with multiple hidden layers, achieved remarkable breakthroughs in areas like computer vision, natural language processing, and speech recognition. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) emerged as influential technologies in this paradigm shift.

1.2. Core Concepts in Machine Learning

Machine Learning encompasses a diverse set of techniques and concepts, each tailored to address specific problem domains and data types. Key components of the Machine Learning framework include:

Data: At the heart of Machine Learning lies data, vast and diverse. Datasets serve as the raw materials for training, validation, and testing of Machine Learning models. These datasets can be structured or unstructured, and their quality and quantity significantly impact model performance.

Algorithms: Machine Learning algorithms form the bedrock of the discipline. These algorithms encompass supervised learning methods for labeled data, unsupervised learning for uncovering patterns in unlabeled data, and reinforcement learning for decision-making in dynamic environments.

Feature Engineering: Feature engineering entails the meticulous selection and transformation of relevant features (variables) from the dataset. Effective feature engineering is often the linchpin for enhancing a model's predictive power.

Model Training: During the training phase, Machine Learning models learn patterns and relationships within the data. This iterative process involves adjusting model parameters to minimize a defined objective function, such as loss or error.

Model Evaluation: The evaluation of a model's performance is a pivotal step. Common evaluation metrics include accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve (AUC-ROC).

Generalization: A fundamental objective in Machine Learning is to achieve generalization, which entails making accurate predictions on unseen data. The challenges of overfitting (where the model is too complex) and underfitting (where the model is too simplistic) necessitate careful model selection and hyperparameter tuning.

1.3. Real-World Applications

Machine Learning's pervasive influence extends to virtually every industry and domain, revolutionizing the way we interact with technology and harness insights from data. Some of the prominent real-world applications include:

Recommendation Systems: E-commerce giants like Amazon and streaming platforms such as Netflix heavily rely on Machine Learning to personalize product recommendations based on user behavior and preferences, enhancing user engagement and satisfaction.

Healthcare: Machine Learning has become a linchpin in medical image analysis, drug discovery, disease diagnosis, and patient outcome prediction. Deep Learning models have demonstrated exceptional accuracy in tasks such as the detection of anomalies in medical images.

Finance: In the financial sector, Machine Learning is indispensable for tasks ranging from fraud detection and algorithmic trading to credit scoring and risk assessment. Predictive models enable financial institutions to identify market trends and investment opportunities in real time.

Natural Language Processing (NLP): NLP techniques empower machines to comprehend, generate, and respond to human language. Chatbots, sentiment analysis, language translation, and automated content generation are but a few manifestations of NLP's transformative capabilities.

Autonomous Vehicles: The realm of autonomous vehicles relies extensively on Machine Learning for real-time perception, decision-making, and navigation. Deep Learning models analyze sensor data to interpret the vehicle's surroundings, enabling safe and efficient autonomous driving.

1.4. Importance and Challenges

Machine Learning's importance cannot be overstated. It has the potential to automate intricate processes, enhance efficiency, and elevate decision-making across a spectrum of industries. In healthcare, Machine Learning assists in diagnosing diseases and optimizing treatment plans, ultimately improving patient care. In manufacturing, predictive maintenance models can reduce downtime and operational costs. In finance, algorithmic trading strategies harness real-time data analysis to make profitable investments.

Nonetheless, Machine Learning is not devoid of its challenges. Issues related to data privacy, ethics, model interpretability, and bias mitigation loom large. The rapid pace of innovation necessitates ongoing learning and adaptation to remain at the forefront of this dynamic field.

In summation, Machine Learning, born out of an aspiration to confer upon machines the power of learning and adaptability, has transcended its origins to become an omnipresent force in diverse industries. From recommendation systems that tailor user experiences to healthcare applications that enhance patient outcomes, the influence of Machine Learning is indelible. This field boasts a rich history, technological marvels, and transformative applications. Yet, it grapples with intricate challenges related to ethics, fairness, and data privacy. As we embark on this exploration, we embark on a journey through the core principles, methodologies, and practical implementations that constitute the captivating world of Machine Learning.

1.5. Machine Learning Algorithm Types

Machine learning is the field dedicated to creating predictive models and algorithms that can extract valuable insights from data, make predictions, and take actions without requiring explicit programming. This domain lies at the heart of artificial intelligence (AI) and involves the study of statistical methods and computer models to enable machines to learn patterns and relationships from data, ultimately using this knowledge to make informed decisions or predictions. The machine learning process typically involves the following key steps:

Data Gathering: The initial step in machine learning involves collecting relevant and comparable data from various sources, which may include structured databases or unstructured data like text, images, and videos.

Supervised Learning: Supervised learning, a branch of computational intelligence, revolves around training algorithms using labeled data to accurately classify data points or predict outcomes. It's akin to teaching a machine to recognize patterns by providing examples with known outcomes.

Unsupervised Learning: Unsupervised learning deals with unlabeled data, aiming to discover inherent patterns and structures within it. Common tasks include clustering data points into groups (clustering) or reducing the data's dimensionality while preserving essential features (dimensionality reduction). For instance, a supermarket might use unsupervised learning to identify purchasing patterns, such as customers who buy grains also buying milk or those purchasing eggs often also buying bacon.

Reinforcement Learning: Reinforcement learning is a machine learning paradigm that focuses on training agents to make decisions in an environment. Agents interact with the environment, receive rewards or penalties based on their actions, and learn through trial and error. It's akin to how a robotic dog learns to move its limbs through repeated actions and feedback.

Big Data Visualization: Big data visualization involves processing and transforming massive datasets into graphical representations that facilitate rapid insights for humans. While it can offer significant advantages, it also presents challenges for organizations dealing with vast amounts of data. Visualizations can range from basic line graphs and pie charts to more sophisticated scatter plots, heat maps, and tree diagrams, depending on the specific needs of the data analysis.

Dimensionality Reduction: Dimensionality reduction, also known as dimension reduction, is the process of converting high-dimensional data into a lower-dimensional space while preserving essential information and structures of the original data. This technique is employed to simplify complex datasets and retain their inherent characteristics in a reduced space, improving computational efficiency and aiding in data analysis.

In essence, machine learning empowers computers to extract knowledge and insights from data, facilitating decision-making and predictive capabilities across various domains and industries. Each facet of machine learning, from data gathering to dimensionality reduction, plays a crucial role in harnessing the power of data-driven intelligence.

2. Methodology

SPSS (Statistical Package for Social Sciences) is a statistical software package widely used for data analysis in various fields, including social sciences, psychology, and market research. While SPSS is primarily known for its capabilities in statistical analysis, it is not typically considered a machine learning platform. Instead, it is more commonly used for traditional statistical methods and data exploration.

However, SPSS can still play a role in the broader context of machine learning and data analysis in the following ways:

Data Preparation: Before applying machine learning algorithms, data preparation is often required. SPSS can be used to clean, preprocess, and transform datasets, making them suitable for input into machine learning models. This includes handling missing data, scaling features, and encoding categorical variables.

Descriptive Statistics: SPSS provides a range of tools for generating descriptive statistics, which can be valuable in the initial exploration of a dataset. Understanding the distribution of data, measures of central tendency, and variability can inform decisions about feature selection and data preprocessing for machine learning.

Feature Selection: SPSS can be used to identify important features or variables that are relevant to a machine learning problem. Techniques like correlation analysis and stepwise regression can assist in feature selection before building machine learning models.

Data Visualization: While not as specialized as dedicated data visualization tools, SPSS can create basic data visualizations like histograms, scatter plots, and bar charts. These visualizations can help analysts gain insights into the data and guide feature engineering choices.

Statistical Testing: SPSS is equipped with a wide range of statistical tests for hypothesis testing and significance analysis. These tests can be useful in understanding relationships between variables and evaluating model performance.

Integration with Machine Learning Tools: SPSS Modeler, an extension of SPSS Statistics, does include some machine learning capabilities. Users can build predictive models using algorithms such as decision trees, support vector machines, and neural networks. However, it's important to note that SPSS Modeler's machine learning functionality may not be as extensive or flexible as dedicated machine learning libraries like scikit-learn in Python or TensorFlow.

In summary, SPSS is a valuable tool for data preparation, descriptive statistics, and traditional statistical analysis, which can be beneficial in the initial stages of a machine learning project. However, for more advanced and specialized machine learning tasks, practitioners often turn to dedicated machine learning libraries and platforms that offer a broader range of algorithms, customization options, and scalability.

3. Result and Analysis

TABLE 1. Descriptive Statistics

	N	Range	Minimum	Maximum	Mean		Std. Deviation	Variance
Machine learning	231	4	1	5	3.68	.062	.948	.898
Supervised Learning	231	4	1	5	3.82	.065	.983	.967
Unsupervised Learning	231	4	1	5	3.63	.070	1.071	1.147
Reinforcement Learning	231	4	1	5	3.80	.065	.989	.978
Big data Visualistaion	231	4	1	5	3.66	.071	1.083	1.172
Dimensionality Reduction	231	4	1	5	3.70	.063	.953	.908
Valid N (listwise)	231							

Table 1 shows the values for descriptive statistics (N), range, lowest to highest mean, and standard deviation Machine learning, Visualisation of Big Data, Supervised Learning, Unsupervised computing Development, Learning by reinforcement, and reduction of dimension also utilizing this.

Table 2: Frequencies Statistics

		Machine learning	Supervised Learning	Unsupervised Learning	Reinforcement Learning	Big data Visualistaion	Dimensionality Reduction
N	Valid	231	231	231	231	231	231
	Missing	0	0	0	0	0	0
Mean		3.68	3.82	3.63	3.80	3.66	3.70
Std. Error of Mean		.062	.065	.070	.065	.071	.063
Median		4.00	4.00	4.00	4.00	4.00	4.00
Mode		4	4	4	4	4	4
Std. Deviation		.948	.983	1.071	.989	1.083	.953
Variance		.898	.967	1.147	.978	1.172	.908
Skewness		-.669	-.680	-.616	-.925	-.539	-.759
Std. Error of Skewness		.160	.160	.160	.160	.160	.160
Kurtosis		.682	.085	-.260	.798	-.410	.619
Std. Error of Kurtosis		.319	.319	.319	.319	.319	.319
Range		4	4	4	4	4	4
Minimum		1	1	1	1	1	1
Maximum		5	5	5	5	5	5
Sum		849	882	839	878	846	854
Percentiles	25	3.00	3.00	3.00	3.00	3.00	3.00
	50	4.00	4.00	4.00	4.00	4.00	4.00
	75	4.00	5.00	4.00	4.00	4.00	4.00

Table 2 Show the Frequency Statistics in for the purposes of machine learning, learning under supervision, reinforcement learning, big data visualisation, and reducing dimensionality curve values, recurrence statistics are provided.

Table 3. Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.571	.572	6

Table 3 shows The Cronbach's Alpha Reliability result. The overall Cronbach's Alpha value for the model is .572 which indicates 57% reliability. From the literature review, the above 50% Cronbach's Alpha value model can be considered for analysis.

Table 4: Reliability Statistic individual

	Cronbach's Alpha if Item Deleted
Machine learning	.458
Supervised Learning	.576
Unsupervised Learning	.483
Reinforcement Learning	.528
Big data Visualistaion	.545
Dimensionality Reduction	.552

Table 4 Shows the Reliability Statistic individual parameter Cronbach's Alpha Reliability results. The machine learning Cronbach's Alpha value. Supervised Learning, Section 458.483: Reinforcement Acquisition; 576: Unsupervised Learning. Big data visualisation scores of 528, 545, and dimensionality reduction scores of 552 show that all parameters may be taken into account for analysis.

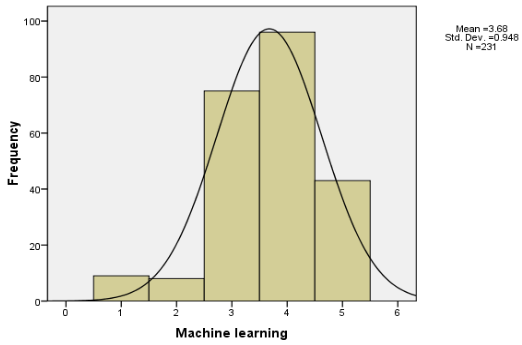

Figure 1. Machine learning

Figure 1 shows the histogram plot for with the exception of the 2 values, all other values are beneath the normal curve, demonstrating that the model is considerably following the normal distribution. Machine learning from the graphic, it is obvious that the data are slightly Right skewed because more respondents chose 4for Machine Learning.

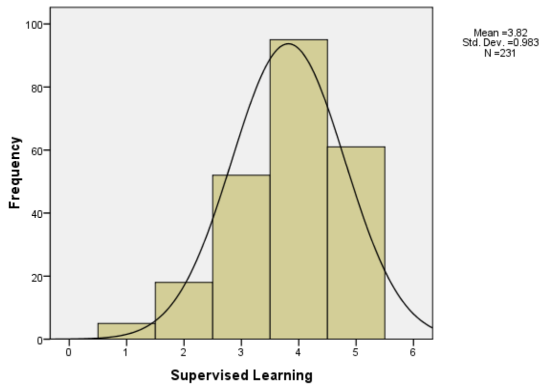

Figure 2. Supervised Learning

Figure 2 shows the histogram plot for supervised education With the exception of the 2 value, all other values are beneath the normal curve, demonstrating that the model is considerably following the normal distribution. As can be observed from the image, the data are slightly right-skewed because more respondents chose 4 for Supervised Learning.

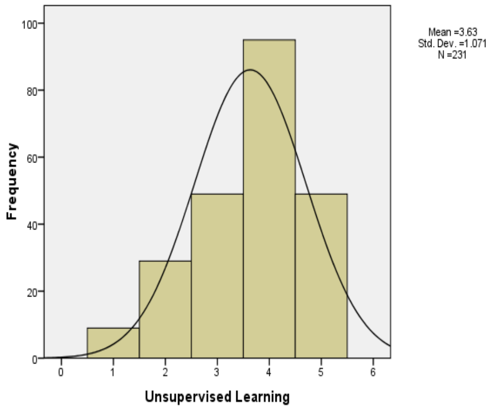

Figure 3. Unsupervised Learning

Figure 3 shows the histogram plot for Unsupervised Education With the exception of the 2 value, which is under the normal curve and indicates that the model is considerably following the normal distribution, it is obvious from the Figure that information that was are slightly right-skewed as a result of more respondents choosing Unsupervised Learning.

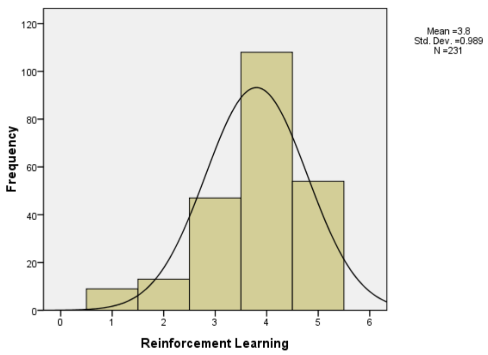

Figure 4. Reinforcement Learning

Figure 4 shows the histogram plot for with the exception of the 2 values, all other values are beneath the normal curve, indicating that the model is considerably following the normal distribution. Reinforcement Learning From the image, it is obvious that the data are slightly right-skewed since more respondents chose 4 for Reinforcement Learning.

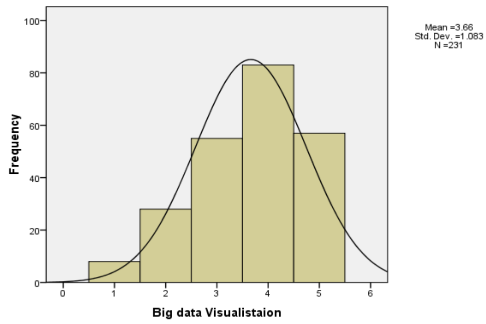

Figure 5. Big data Visualization

Figure 5 shows the Big data Visualization exception of the 2 value, all other values in the histogram plot for big data visualisation are under the normal curve, indicating that the model is significantly following the normal distribution. This is because more respondents chose option 4 for big data visualization.

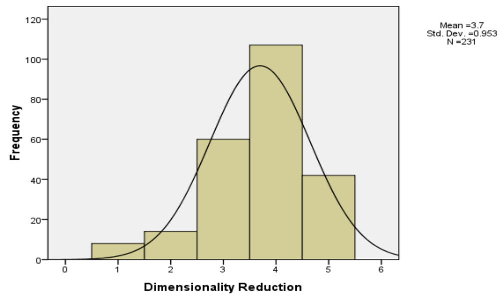

Figure 6. Dimensionality Reduction

Figure 6 shows the histogram plot for Diminished Dimensions With the exception of the 2 value, all other values are beneath the normal curve, demonstrating that the model is considerably following the normal distribution. As can be observed from the image, the data are slightly right-skewed because more respondents chose 4 for dimensionality reduction.

Table 5: Correlations

	Machine learning	Supervised Learning	Unsupervised Learning	Reinforcement Learning	Big data Visualization	Dimensionality Reduction
Machine learning	1	.179**	.396**	.255**	.278**	.184**
Supervised Learning	.179**	1	.130*	.012	.077	.192**
Unsupervised Learning	.396**	.130*	1	.382**	.159*	.073
Reinforcement Learning	.255**	.012	.382**	1	.120	.116
Big data Visualistaion	.278**	.077	.159*	.120	1	.179**
Dimensionality Reduction	.184**	.192**	.073	.116	.179**	1
**. Correlation is significant at the 0.01 level (2-tailed).						
*. Correlation is significant at the 0.05 level (2-tailed).						

Table 5 shows the correlation between motivation parameters for computer learning. Unsupervised learning and Dimensionality Reduction have the largest and lowest correlations, respectively. The relationship between the dimensions of motivation for supervised learning is next. For instance, Reinforcement Learning and Dimensionality Reduction have the highest and lowest correlations, respectively. The correlation between the parameters that drive unsupervised learning comes next. Machine learning and Dimensionality Reduction have the strongest and lowest correlations, respectively. The association between reinforcement learning motivational parameters is the next topic. In contrast to supervised learning, which has a lower correlation, unsupervised learning has a higher correlation. The association between big data visualization motivational parameters follows. In contrast to supervised learning, which has the lowest correlation, machine learning has the highest correlation. The association between the dimensions of motivation for Dimensionality Reduction follows. In contrast to unsupervised learning, which has the lowest correlation, supervised learning has the highest correlation.

4. Conclusion

Machine Learning in the field of Computer Science emulates human learning processes, aiming to enhance accuracy gradually. IBM boasts a rich history in artificial intelligence, with Arthur Samuel coining the term "machine learning" in 1959, defining it as the discipline enabling algorithms to learn autonomously, devoid of explicit programming. This paradigm belongs to computational intelligence, liberating robots from the confines of coding, allowing them to glean knowledge from experience.

A common challenge tackled by machine learning is recommendation systems, as evidenced in Netflix's ability to curate personalized movie and TV show suggestions. This feat blends aggregate filtering with content-based filtering, with the potential for enhancement through reinforcement learning.

Machine learning serves as an approach that employs algorithms to construct automated statistical models, iteratively learning from data. Supervised learning, a branch of computational intelligence, stands out as it trains algorithms to accurately classify data and predict outcomes using labeled data.

Remarkably, machines now possess the capacity to uncover concealed insights without explicit instruction, thanks to machine learning. Semi-supervised learning, or independent learning, aptly characterizes this capability, revealing latent patterns and structures in data, even in the absence of explicit labels.

In essence, machine learning revolves around creating predictive models and algorithms capable of gleaning insights and making informed decisions autonomously, with roots deep in the domain of artificial intelligence. To enable machines to discern connections and patterns from data and use this knowledge for informed predictions, it necessitates the study of statistical methods and computer models. The Cronbach's Alpha Reliability result, indicating a 57% reliability with an overall Cronbach's Alpha value of .572, underscores the significance of rigorous statistical analysis. This reassures the suitability of machine learning models, guided by findings from a comprehensive literature review, where models with Cronbach's Alpha values exceeding 50% merit further analysis.

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