Machine Learning-Based Predictive Analytics for Sustainable Renewable Energy Investments

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Abstract: Renewable energy investments are crucial to address climate change effectively, reduce environmental impacts, and promote sustainable economic growth globally. Investing in renewable energy markets, however, presents many challenges due to their inherent complexity, market volatility, regulatory uncertainties, and unpredictability in technological advancements. This study was conducted to examine how machine learning-based predictive analytics can assist in making sustainable investments in renewable energy sources. This work evaluates the performance of multiple classifiers, including Logistic Regression, SVM, C4.5, KNN, LSTM, and Bayesian Networks, using metrics like prediction accuracy and class distribution analysis. According to this study, advanced investment strategies in the renewable energy sector can be significantly optimized by employing sophisticated predictive models, such as Long Short-Term Memory (LSTM) networks and Bayesian networks. The authors emphasize the critical importance of developing intelligent data-driven decision-making frameworks capable of effectively addressing class imbalance challenges, enhancing data quality, and delivering precise, actionable insights to facilitate strategic investments that accelerate global renewable energy adoption.

1 INTRODUCTION

Investing and innovating in sustainable energy sources are among the most dynamic sectors for mitigating climate change. Due to fluctuating resource availability, evolving regulatory landscapes, and rapid technological advancements, the renewable energy market is characterized by significant uncertainty. Traditional investment analysis methods do not provide accurate forecasts of returns and risks in this complex environment. Predictive analytics based on machine learning offer enhanced capabilities to model intricate patterns, assess investment viability, and optimize decision-making. By using vast datasets and sophisticated algorithms, machine learning makes it possible to predict market trends, energy outputs, and financial performance more accurately, supporting more informed and sustainable investments. Adding advanced analytics to renewable energy finance not only promises improved economic outcomes but also accelerates the global shift toward more sustainable and resilient energy sources [1].

Renewable energy has been thrust to the forefront of global policy and investment agendas due to the growing urgency of climate change and the depletion of fossil fuel resources. Renewable energy sources like solar, wind, hydro, and bioenergy are essential to achieving environmental goals, reducing greenhouse gas emissions, and spurring economic growth. Investments in renewable energy projects, however, are inherently complex due to factors such as resource intermittency, regulatory uncertainty, technological development, and market volatility. Traditionally, financial and risk assessment models don't take into account the dynamic and nonlinear influences on renewable energy investments.

Many industries have benefited from the rapid progress of AI and machine learning, including the energy sector [2], [3]. Renewable and sustainable energy solutions have become increasingly important as climate change and environmental degradation pose urgent challenges to the global community [4], [5]. Fossil fuel-dependent energy systems cannot be sustained due to their damaging impact on the environment and limited availability. This scenario demonstrates how AI and ML can revolutionize the renewable energy industry by enhancing resource management, increasing efficiency, and promoting sustainable energy strategies [6], [7], [8]. AI and machine learning are primarily used in renewable energy plans because of their ability to analyze large datasets, forecast results, and improve processes immediately. To be able to cope with the unpredictable and rapidly changing characteristics of solar and wind energy, these technologies must be put in place for renewable energy sources. Artificial intelligence algorithms are capable of predicting weather patterns and solar radiation with high accuracy, which allows solar energy systems to be seamlessly integrated into the grid. In the same way, ML models are capable of forecasting wind speeds and power generation, which improves grid management and energy allocation. With more and more renewable energy sources becoming more prevalent, these functions are crucial to maintaining stability and reliability.

The renewable energy industry heavily relies on AI and machine learning, especially when it comes to energy storage and grid management [9]. Energy storage devices such as batteries are essential to managing the fluctuations of renewable energy sources. As storage systems age, artificial intelligence can improve their charging and discharging processes, resulting in longer lifespans and greater efficiency. Furthermore, artificial intelligence can be used to improve grid control by predicting energy supply and demand, thereby improving both efficiency and reliability. Additionally, this reduces operational expenses, improves the durability of energy systems, and decreases energy loss [10]. As AI and machine learning optimize energy usage in different industries, they have a significant impact on improving energy efficiency [11]. Smart grids powered by artificial intelligence can adapt energy distribution based on current data, reducing energy losses and optimizing energy use in critical locations.

Furthermore, AI-powered energy management systems can analyze patterns of energy consumption in buildings and industrial facilities. Based on the results of this analysis, automated adjustments can be made to reduce consumption and identify opportunities for energy savings. The implementation of these systems results in substantial cost savings and contributes to the achievement of wider sustainability objectives [12].

In addition to reducing environmental damage and improving residents' well-being, artificial intelligence and machine learning are also used to develop smart cities [13]. The implementation of AI-based solutions in smart cities benefits sustainable urban development by improving waste management, optimizing energy usage, and boosting transportation systems [14]. Artificial Intelligence algorithms, for example, can improve traffic flow, ultimately reducing emissions and congestion. In contrast, machine learning can forecast patterns of waste generation, resulting in more efficient recycling and waste disposal. Smart buildings and infrastructure utilize energy management systems powered by AI to optimize energy consumption, improving urban sustainability in the process [15]. There are many advantages to incorporating AI and machine learning into renewable energy plans, but there are also challenges that must be overcome. The requirement for top-notch, instantaneous data to train AI and ML models poses a significant challenge. In the energy industry, gathering and managing data can take significant resources and be complex, so substantial investments are needed to build a strong infrastructure [16]. It is also necessary to have a competent team able to design, develop, implement, and support these sophisticated technologies in order to implement AI-based solutions. Achieving sustainable energy solutions requires tackling these challenges in order to utilize AI and ML fully.

Furthermore, AI in the energy industry should be viewed in light of its ethical and regulatory implications. AI algorithms require addressing biases, data privacy, and security [17]. Developing guidelines for utilizing AI responsibly and fairly will ensure widespread benefits while reducing risks, which is why the energy industry and policymakers should work together to develop them.

2 LITERATURE REVIEW

As solar farms become increasingly reliable and efficient, predictive maintenance (PdM) is becoming an important strategy for optimizing performance and reliability. Advanced data analytics and machine learning techniques are used to forecast equipment failures and proactively address maintenance costs. The purpose of this section is to provide a comprehensive overview of the literature on predictive maintenance in solar farms, including seminal works, recent works, and comparative analyses across diverse technological contexts and geographical locations [18].

The rapid expansion of solar energy installations across the globe has highlighted the importance of predictive maintenance in improving solar farm reliability and performance. As part of his study [19], the Author evaluated the effectiveness of predictive, preventative, and corrective maintenance strategies in solar farms to maximize equipment uptime and minimize operational disruptions. As a result of their research, predictive maintenance proved to be more cost-effective and efficient than reactive maintenance.

Comparative studies have also shown that machine learning-based predictive maintenance algorithms outperform conventional rule-based maintenance algorithms. In a study by the Author [20], supervised learning algorithms were compared to unsupervised learning algorithms to predict solar panel failure, with machine learning models proving to be more accurate and predictive than supervised learning algorithms. Using historical performance data and sensor measurements, machine learning algorithms can identify subtle proactive intervention strategies to avoid downtime and optimize maintenance schedules in order to prevent equipment failures.

Solar farms have also been investigated for their economic and environmental impacts in addition to their technical considerations. According to Author [21], life cycle cost analyses (LCCAs) were conducted on solar energy systems to evaluate the viability of predictive maintenance investments in the long run. According to their findings, predictive maintenance is initially more expensive than reactive maintenance, but the cost savings and performance improvements over the lifetime of the asset outweigh the upfront costs. Furthermore, predictive maintenance can reduce the environmental footprint of solar energy operations by reducing waste generation, resource consumption, and greenhouse gas emissions associated with unscheduled downtime.

Using reinforcement learning control strategies [11], research has developed a method of reducing energy consumption and losses in the distribution sector. Solar energy for heating, biomass boilers, and photovoltaic solar cells are among the most efficient sources of renewable energy. A building's energy consumption determines control systems, what is saved for later use or released into the environment, and what has the least impact on the environment. Building management system optimization is achieved using a unique technology called BEEL. A combination of vector-wavelet-based training algorithms is compared with the described reinforcement learning method to maximize mathematical rewards. Compared to the prior ML methods, the novel method shows better compliance and reward-based actions. Compared to artificial intelligence, reinforcement learning is 99.98% accurate and can be used in conjunction with trial and error and delayed rewards.

According to [22], 100% renewable energy is suitable for desalination, transportation, heat, and electricity. For 145 local energy systems split into nine key global sectors, a technologically sophisticated, cross-sectoral, cross-regional, and financially advantageous global energy transformation pathway is presented. There are several benefits to a 1.5 °C target-compatible situation, including widespread access to fresh water, 50% energy savings, and low energy costs. The plan also involves the rapid indirect and direct electrification of DE through Power-to-X processes and the massive fossilization of DE. Moreover, it offers a pathway to an efficient, reliable, and sustainable energy system that replaces fossil fuels with renewable energy sources. Even though renewable energy facilities, such as solar power plants, wind turbines, and energy storage facilities, have potential long-term benefits, they can be extremely costly to build. Developing nations or areas heavily reliant on fossil fuels may face obstacles due to a lack of financial resources [23].

Using modified trihybrid nanoparticles, the Author [24] proposed a model to describe blood flow in stenotic/dilating arteries. Using homology perturbation, we solve the equations using a fractional fluid model that accounts for blood's non-Newtonian behaviour. Even though the fractional parameter limits the model's clinical applicability, it still provides valuable information. According to the Author, weakly conducting fluids flow through porous structures when an electromagnetic plate oscillates [25]. In the Darcy model, larger Darcy numbers reduced velocity, while higher modified Hartmann numbers increased velocity. Key flow quantities are accurately predicted by their ANN model with a 99.95% accuracy rate.

3 METHODOLOGY

3.1 Exclusion Criteria

Any area outside of Greece's EEZ is legally excluded from the study area. As of the early 2000s, national territorial waters have been considered as a siting criterion, as well as the EEZ of a country [26] - [28]. We discuss the exclusion criteria used in this paper in the following section.

3.1.1 Wind Velocity

Site selection for an OWF is heavily influenced by wind velocity, as it directly impacts economic feasibility. Wind data analysis is therefore vital for assessing potential wind energy sites based on their wind data accuracy and detail. An hourly wind velocity measurement at 80 m height has been made for the last 10 years (2009-2018) and is used to calculate the wind velocity in this study. The present site suitability analysis concludes that OWFs should not be located in marine areas with average wind speeds less than 6 m/s at an elevation of 80 m above mean water level [29].

3.1.2 Water Depth

When OWFs are sited, their investment costs are significantly influenced by the depth of the water [30]. A wind turbine's support structure and its CAPEX and OPEX are significantly affected by the water depth, which increases significantly in deeper waters. Based on [31], it can be assumed that deeper waters incur higher costs due to mooring, anchoring, and cabling expenses. There is a 500 m maximum limit on the depth of the water in this investigation [29].

3.1.3 Military Zones

Neither the National Army nor the Marines use these marine areas for any other purpose than for training purposes. Taking into account the current criterion [28].

3.1.4 Seismic Hazard Zones

When selecting a construction site, seismic hazards should be taken into consideration. Globally, Greece has one of the highest seismic activity rates. Therefore, all infrastructure should be earthquake-resistant. Wind turbine supporting structures may have to be specially designed for OWFs, resulting in higher construction costs. Consequently, seismic hazards (0.36g) in Greece are excluded. OWF site selection has not been included in any other study of OWF sites that are internationally seated. Still, it was proposed by [32] as a criterion for selecting suitable sites for OWF developments in South Korea, but it wasn't included in their study.

3.1.5 Underwater Cables

Cables that are already on the seafloor and are either telecommunications or electrical transmission cables are excluded from this criterion [28]. The underwater cable routes must be taken into account when installing OWF developments.

3.2 Intelligent Predictive Analytics Inference Model

Intelligent predictive inference models are based on machine learning classification algorithms. According to the nature of the predicted output, these algorithms can be divided into two major categories.

There are two categories of scenarios: numerical and qualitative. Regression is the machine learning method used in such cases.

Classification, on the other hand, applies when a categorical value is predicted, in which case the process is referred to as classification. In addition to classification, there are two subcategories based on the number of possible classes:

When a categorical variable only has two possible classes, it is called binary classification.

3.3 Multiclass Classification of Categorical Variables and Fold Cross-Validation Techniques

During this study, 10-fold cross-validation was used to enhance the effectiveness of the training of the models. The tenfold algorithm divides data input into ten subgroups. The training data is based on nine subgroups, and the test data is based on the remaining subgroup. To reduce bias, the models are trained for 10 iterations using data. Additionally, the model weights for convolutional layers are continuously updated in every iteration, increasing the effectiveness of training. A common design for a k-fold can be seen in Figure 1. To train the model for this study, k = 10 subgroups of input data are divided and trained for 10 iterations.

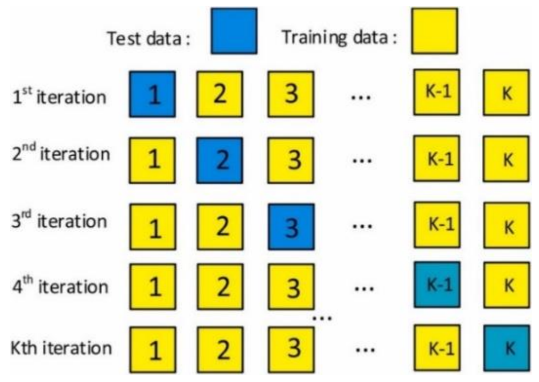

Figure 1: 10-fold-cross-validation process.

3.4 Evaluation Metrics in Classification

A description of performance evaluation metrics used in most machine learning applications for classification, including how and why they are used.

3.4.1 Prediction Accuracy

Prediction accuracy of a machine learning model reflects its ability to correctly predict unseen data. According to [33], accuracy is calculated as the proportion of correct predictions (both positive and negative) relative to all predictions made by the model. The calculation incorporates four fundamental classification outcomes: true positives (TP) represent instances correctly predicted as positive, true negatives (TN) represent instances correctly predicted as negative, false positives (FP) represent negative instances incorrectly predicted as positive, and false negatives (FN) represent positive instances incorrectly predicted as negative. This metric provides an overall measure of model correctness across all classification decisions.

3.4.2 Confusion Matrix

A confusion matrix was first created by Karl Pearson in 1904 when it was known as a contingency table. In data science, it has been called a confusion matrix before a classification matrix. We should have kept the name "classification matrix" since it is more accurate and eliminates a lot of confusion. During the process of improving the model, there may be confusion over a specific metric to prioritize, even though the confusion matrix provides several metrics to consider. There are N output classes in the confusion matrix, and N is its size, where N denotes the number of input classes. There are rows representing predictions and columns representing actual classes in the matrix. An analysis of the accuracy and accuracy of a classifier's predictions for classification tasks is given in this table. There are binary and multiclass categorizations. Classifier performance can be assessed from the confusion matrix, which reveals what the classifier gets right and what it can do wrong. Through the confusion matrix, the best course of action can be determined to improve the model. Confidence matrices are used in supervised learning methods since they can be constructed for datasets with known outcomes.

3.4.3 Normalization

The normalization of traffic feature values is also necessary to convert independent features into a specific range of values. Data mining and data analysis use this technique to normalize features. A normalization step can suppress the very large values resulting from feature extraction from network traffic. By using the min-max method, these values can be linearly normalized between 0 and 1, which can be calculated as follows:

$$d_{ij} = \frac{d_{ij} - \min(d_{ij})}{max(d_{ij}) - \min\,(d_{ij})}. \quad (2)$$

Row i and column j of dataset d represent the value of d_{ij}.

3.5 Training Machine Learning Classifiers

Our study aims to achieve its objectives by training a baseline classifier with a variety of kernel functions. In addition, there are several other classifiers, including Logistic Regression (LR), SVM (SVM), C4.5 (C4.5), LSTM (LSTM Deep Learning Recurrent Neural Networks) and Bayesian Networks (Bayesian Networks). As part of the training process, we use training datasets to build trained models, which we will then use as part of the next step.

3.6 Testing Machine Learning Classifiers

The purpose of this step is to train models on an unknown dataset. In the study, it was a straightforward process to determine whether the machine learning classifiers were successful. Input network traffic features have actual class labels. A training dataset is used to train the classifier models, and then the results are compared to the actual labels in the dataset. It is classified correctly if the two are the same, and we move on to the next test example if they are. A classification that does not match is deemed incorrect. This step involves setting up network intrusion detection performance metrics.

4 RESULTS AND DISCUSSION

Figure 2 presents a comparison of the predicted accuracy of six different machine learning classifiers, including Logistic Regression (LR), Support Vector Machine (SVM), decision trees based on C4.5, K-Nearest Neighbors (KNN), Long Short-Term Memory (LSTM), and Bayesian Networks (BN). Using a percentage (%) as a measure of prediction accuracy, classifiers are measured according to their performance. There is a significant variation in accuracy among the five models, with BN achieving the highest accuracy at 79.42%, followed closely by LSTM (77.36%) and KNN (76.54), and LR recording the lowest accuracy at 70.36%. Even though all classifiers perform reasonably well, advanced models like LSTM and BN provide superior predictive capabilities compared to traditional methods like LR and SVM. This highlights their potential effectiveness in complex predictive analytics.

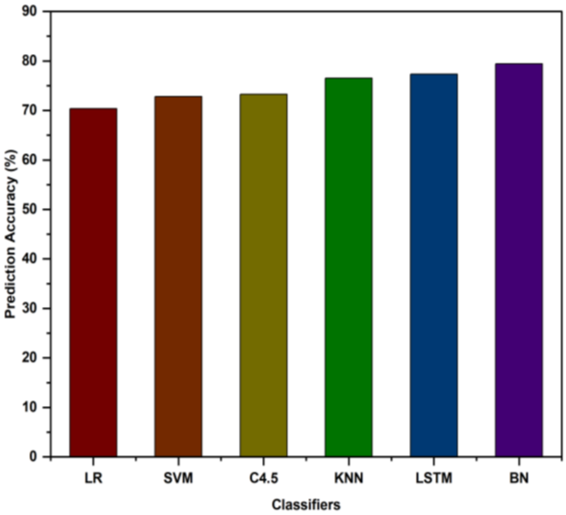

Figure 2: Accuracy of classifier predictions.

Figure 3 depicts the distribution of predictions across two classes, 0 and Class 1-for six different classifiers (LR, SVM, C4.5, KNN, LSTM, and BN) in relation to investments in renewable energy (RES). There is a significant dominance of class 0, represented in brown, across all classifiers, indicating that the majority of predictions fall into this category. All models predict Class 1 relatively few times, with SVM showing slightly higher numbers than other models. It may be an underlying class imbalance in the dataset or that the models are not able to identify investment opportunities (Class 1) in renewable energy as a result of the imbalance between Class 0 and Class 1.

According to Figure 4, six machine learning classifiers were used to classify the "Not Invest in Renewable Energy Sources (RES)" category: LR, SVM, C4.5, KNN, LSTM, and BN. For most model classifications, Class 0 (brown) consistently predicts non-investment decisions more accurately than Class 1 (green). As one of the most prominent features of the C4.5 classifier, almost no predictions are made for Class 1 as a result of the extreme skew towards Class 0. SVMs and LSTMs demonstrate somewhat better balance, though Class 0 continues to dominate. As a result, classifiers predict non-investment outcomes more accurately, even when class imbalances and subtle factors influencing investment decisions are present.

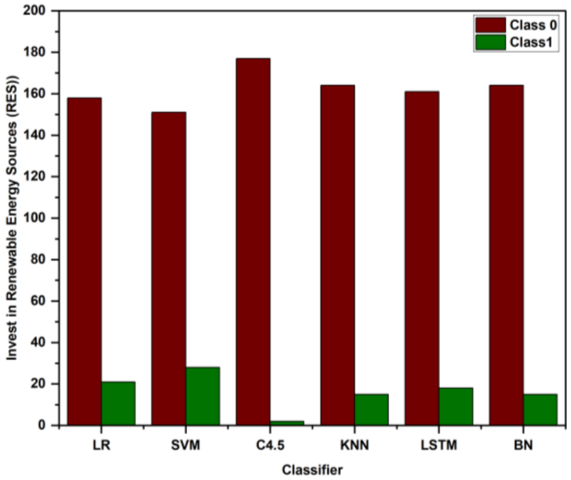

Figure 3: Class-wise prediction results for renewable energy investments.

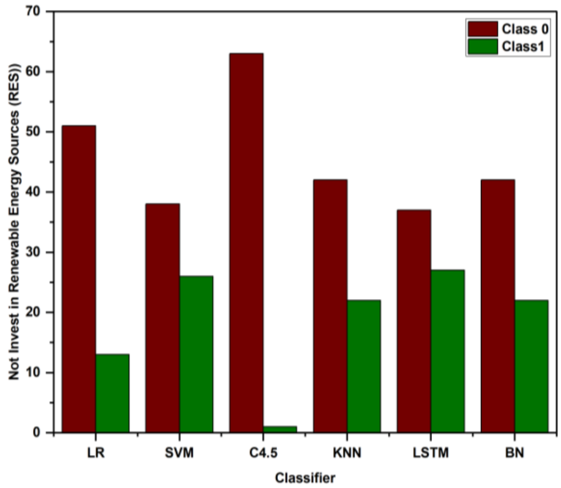

Figure 4: Prediction distribution for non-investment in renewable energy.

5 CONCLUSIONS

Using machine learning to predict renewable energy investment decisions can significantly improve investment decisions. Bayesian networks and LSTM models performed the best among the six classifiers evaluated, demonstrating their superior abilities to model complex relationships in renewable energy data. Using the class distribution analysis, it was revealed that non-investment predictions were dominant, suggesting that dataset imbalance and the complexity of identifying promising investment opportunities are challenges. Machine learning, however, can significantly enhance the accuracy of forecasts, optimize resource management strategies, and improve financial planning associated with sustainable energy projects by effectively capturing complex patterns and trends. Achieving a greener, more sustainable energy future will necessitate machine learning techniques capable of integrating broader, diverse datasets, addressing class imbalances, reducing predictive uncertainty, and enhancing decision-making reliability.

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