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Enhancing Energy Efficiency in Smart Cities: Advanced ANN and Decision Tree Model for Solar Energy with IoT and Cloud Server

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Abstract: In the current era of climate change challenges, employing data analysis and Machine Learning (ML) techniques has become crucial in generating precise forecasts to optimize energy consumption. Efficiency factors like solar irradiance, clear skies, clean panels, and unobstructed sun exposure play crucial roles. Using sensors for monitoring and IoT for remote accessibility, solar power systems incorporate smart technology connected to Arduinos for continuous panel parameter monitoring. This research predominantly focuses on Energy Load Forecasting in the smart city environment, developing and comparing hybrid deep learning model using historical data from a near Zero Energy Building. The dataset comprises energy load and temperature metrics, shaping various ML algorithms such as Artificial Neural Networks and Decision-trees, tailored to unique data features like the presence of photovoltaics. A groundbreaking hybrid model, amalgamating outputs from multiple ML algorithms, has been introduced, resulting in a meta-model voting regressor that standardizes new data inputs. Experimental evaluations against unseen data and alternative ensemble methods displayed promising forecasting results, exhibiting superior performance compared to base algorithms.

Keywords: *Machine Learning, Energy Load Forecasting, Sensors, Internet of Things, photovoltaic*

1. Introduction

This template, Smart solar system management is a comprehensive approach that encompasses a multitude of methodologies and technologies geared toward enhancing the performance, supervision, and regulation of solar power systems. These methodologies seamlessly intertwine state-of-the-art technologies, such as Artificial Intelligence (AI), Internet of Things (IoT), machine learning, and data analytics, to facilitate efficiency and control. Key methods in smart solar system management include the application of AI techniques for predictive analysis, fault detection, and optimal solar power generation. Employing machine learning algorithms such as Artificial Neural Networks and Decision Trees allows for forecasting, pattern recognition, and predictive maintenance. Additionally, the integration of IoT technology fosters connectivity between solar panels, sensors, and system components, enabling real-time monitoring, remote access, and data collection, thereby boosting system efficiency and performance. Predictive analytics uses historical data and machine learning models to predict solar energy production, energy usage patterns, and maintenance requirements. Remote monitoring and control, facilitated by sensor-equipped systems and automated controls, permit real-time adjustments in response to varying weather conditions, energy demands, and grid statuses.

Big data management and cloud computing are crucial in managing extensive data, offering storage, analysis, and information retrieval. Furthermore, energy storage solutions like battery systems ensure a balanced energy supply and demand, guaranteeing continuous power availability. Optimization algorithms optimize system parameters, such as the tilt angles of solar panels, to maximize energy output. Integrating microgrids and distributed energy resources is vital for efficient energy distribution and utilization, while weather forecasting integration aids in system setting adjustments for energy production fluctuations. Smart inverters play a critical role in improving grid stability, integrating solar systems into the grid, and enabling two-way communication for optimized energy flow. These methodologies collectively play pivotal roles in managing and optimizing smart solar systems, with the shared goal of enhancing efficiency, reducing costs, and ensuring sustainable energy production and utilization. The integration of these techniques is fundamental for the successful operation and performance of smart solar systems.

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In the contemporary landscape of energy sustainability and climate change, the implementation of data analysis and Machine Learning (ML) methodologies stands as an indispensable tool for the precision forecasting and optimization of energy consumption. Addressing the vital factors of efficiency such as solar irradiance, clear skies, clean panels, and uninterrupted sun exposure , has become a pivotal focus in ensuring effective utilization of energy resources. The integration of sensors for real-time monitoring and Internet of Things (IoT) technologies for remote accessibility has revolutionized solar power systems. These systems are interlinked with Arduinos, allowing continuous monitoring of various parameters critical for optimal energy generation.This research primarily centers on Energy Load Forecasting within the context of a smart city environment. It seeks to develop and compare a hybrid deep learning model, utilizing historical data sourced from a near Zero Energy Building, thereby focusing on crucial datasets comprising energy load and temperature metrics. The inclusion of distinct data features, such as the presence of photovoltaics, necessitates the tailoring of diverse ML algorithms. These algorithms range from Artificial Neural Networks to Decision-trees, forming the basis of the hybrid model.

The innovative approach integrates multiple ML algorithm outputs into a meta-model voting regressor, a pioneering concept. This regressor standardizes new data inputs, fostering a comprehensive and accurate forecasting framework. This hybrid model aims to improve energy load forecasting accuracy while adapting to diverse data inputs. Rigorous experimental evaluations validate its effectiveness, showcasing superior performance compared to standard algorithms. Representing a significant stride in energy forecasting, this model leverages deep learning to cater to specific data nuances, like photovoltaics, promising a transformative strategy for smarter city energy management. Its application contributes significantly to sustainable energy practices and advanced management in smart city environments.

2.Related Works

Comprehensive view of the evolving landscape in the integration of advanced technologies into the realm of solar energy and smart grids. Together, artificial intelligence and machine learning offer a plethora of information about how cutting-edge methods are being applied to maximise the sustainability, dependability, and efficiency of solar energy systems Table-I

Regarding Digital Transformation and Energy, [1] examine the useful uses of digital twins in various industries, whereas [2] focus on the consequences of utilising digital twin technology in the energy industry. Furthermore, [3] explores industry 4.0, blockchain, and digitization in relation to managing energy companies. [4] concentrate on examining peer-to-peer energy trading price schemes designed to promote sustainability in the energy industry.

Turning our focus to sustainability and energy management, the following research provide insightful information: [5] look into energy management in multi-microgrid systems; [6] talk about green investment and technological advancement for sustainable development; [7] stress diversification to ensure a stable supply of energy during the transitional period; [8] concentrate on the implications of equity and sustainability for the urban energy-mobility nexus; and [9] focus on ecologically sustainable production by recycling photovoltaic panels Many studies have explored the intersection of IoT, artificial intelligence, and smart cities. For example, Tang and colleagues [10] provide optimisation strategies for multi-objective distributed hybrid flow shop scheduling, while [11] investigate artificial intelligence system detection in English teaching using genetic algorithms. Other studies [12] concentrate on integrating IoT and AI for advancement in smart city scenarios, [13] provide an overview of demand-side energy management customised for smart grids, [14] address managing COVID-19-related knowledge from a smart city perspective, and [15] describe the planning and execution of an IoT-based smart energy management system. In the field of photovoltaic systems and solar power, research focuses on several aspects: In order to better understand the impact of smart city construction on energy conservation and CO2 emissions reduction in China, [16] conducts a systematic review of smart windows technologies with a focus on electrochromics; [17] reviews the regional energy internet within smart cities from the perspective of the energy community; and [20] forecasts electricity consumption and production in smart homes using statistical methods.

Finally, there are several facets to the discussion of control and optimisation of solar photovoltaic systems: [21] emphasise the operation of an intelligent control system for solar plants under varying insolation; [22] introduce a deep reinforcement learning method for Maximum Power Point Tracking (MPPT) in PV systems that are partially shaded; [23] present an improved Bayesian-based MPPT controller for PV systems; [24] describe solar photovoltaic power forecasting using a modified extreme learning machine technique; and [25] talk about MPPT control schemes for PV systems within microgrids that are nonlinear adaptive NeuroFuzzy feedback linearization-based. When taken as a whole, these articles contribute to the conversation on energy management, digital transformation, smart city technologies, and solar power optimisation by covering a variety of topics within the larger energy industry. optimising solar photovoltaic (PV) system performance under various shading scenarios. To improve PV systems, for example, [26] focuses on developing a Neuro-Fuzzy

Wavelet-Based Adaptive MPPT Algorithm. In the meanwhile, in order to evaluate the effectiveness of reconfigurable PV modules under shadowing, [27] does a cost-benefit analysis. Conversely, [28] offers a thorough analysis of reconfigurable solar photovoltaic systems, thoroughly examining their possibilities.

In a similar spirit, [29] focuses on maximising power extraction from solar PV array reconfiguration using a genetic algorithm when partial shade occurs. Furthermore, [30] focuses on rearranging the PV arrays in order to mitigate the negative impacts of partial shade on PV systems. Collectively, these papers include a range of techniques and tactical insights for PV system reconfiguration, which is essential for maximising performance in a variety of shading scenarios for solar photovoltaic systems. Together, they provide a plethora of knowledge, with each piece offering unique solutions to the problems caused by shading in relation to solar photovoltaic systems.

Table 1 – Comparative examination of diverse methodologies applied in the management of intelligent solar systems.

Ref No	**Method Used**	**Parameters Used**	**Application/Area of Focus**
[1]	Digital Twins	Industrial data, models	Industrial Applications of Digital Twins
[2]	Digital Twin Technology	Energy sector analysis, technological advancements	Digital Revolution in the Energy Sector
[3]	Digitization, Blockchain, Industry 4.0	Enterprise management, digitization strategies	Management Processes in Energy Sector Enterprises
[4]	Peer-to-Peer Energy Trading	Energy pricing mechanisms, sustainability parameters	Sustainable Energy Sector Analysis
[5]	Energy Management in Multi-Microgrid Systems	Microgrid data, power management	Multi-Microgrid Energy Management
[6]	Green Investment and Technological Progress	Sustainability metrics, technological advancements	Green Industrial Development
[7]	Diversification	Energy supply sustainability, diversification strategies	Ensuring Sustainable Energy Supply
[8]	Urban Energy-Mobility Nexus Transformation	Urban energy-mobility data, sustainability metrics	Sustainability and Equity in Urban Energy
[9]	Recycling Photovoltaic Panels	Production line data, recycling process models	Ecological Sustainable Production
[10]	Multi-class teaching–learning-based optimization	Scheduling optimization data	Multi-Objective Hybrid Flow Shop Scheduling
[11]	Artificial Intelligence System Detection	Heuristic Genetic Algorithm, educational data	AI in English Teaching
[12]	Integration of IoT and AI	Smart city technology, recent advancements	IoT-Enabled Smart City Solutions
[13]	Demand Side Energy Management	Grid management, energy solutions	Smart Grid Energy Management
[14]	Managing COVID-19-related knowledge	Smart city knowledge management, pandemic response	COVID-19 in Smart Cities
[15]	IoT-Based Smart Energy Management	IoT data, energy management techniques	IoT-Enabled Energy Management

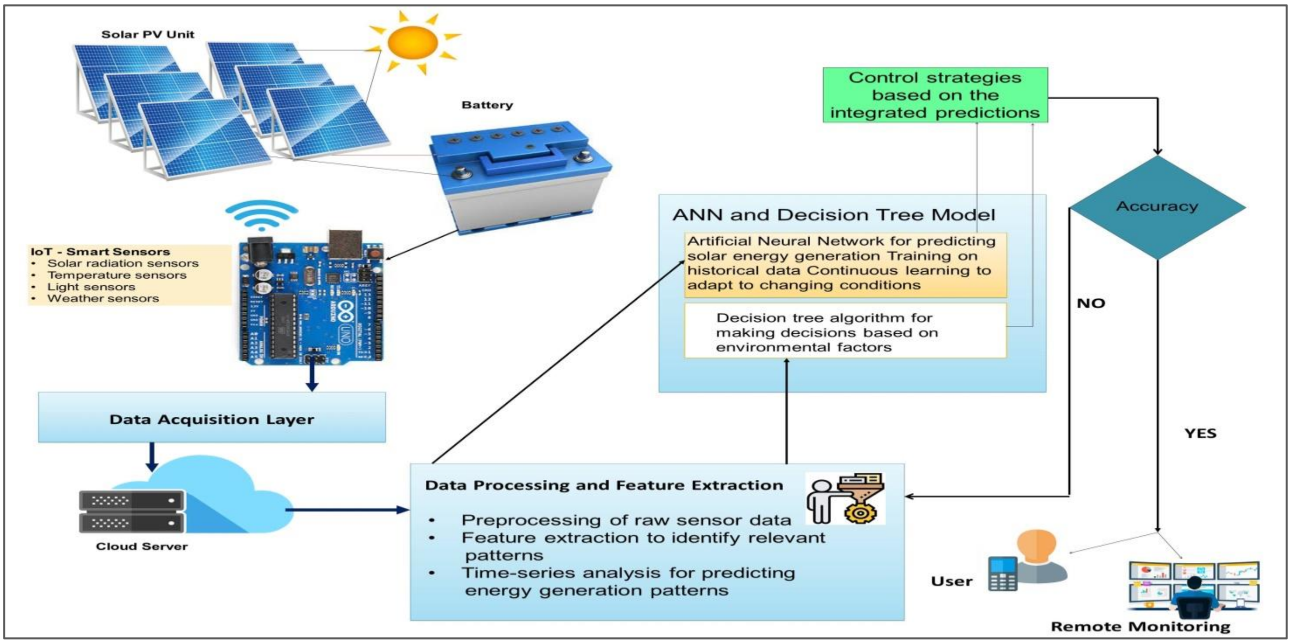

Fig 1- Proposed system Architecture

3. Proposed Methodology

3.1 Methodology

The method employed (Figure-1) in this context involves leveraging data analytics and Machine Learning (ML) as key tools to tackle the challenges of climate change by optimizing energy consumption. It particularly focuses on Energy Load Forecasting in a smart city setup. The research develops and compares a hybrid deep learning model utilizing historical data from a near Zero Energy Building. This data encompasses energy load and temperature metrics, which are used to tailor various ML algorithms, such as Artificial Neural Networks and Decision-trees, to accommodate unique features like photovoltaics in the dataset. The innovative aspect of this research lies in the creation of a hybrid model that combines the outputs from multiple ML algorithms. This amalgamation culminates in a meta-model voting regressor designed to standardize new data inputs for more accurate forecasting.

3.2 Hybrid Machine Learning Model

This model under consideration adopts a sophisticated hybrid deep learning strategy that amalgamates multiple pivotal techniques. This integrative approach encompasses the utilization of Artificial Neural Networks (ANNs), Decision Trees, and attention mechanisms. These elements combined form a comprehensive and dynamic framework for predictive analysis and advanced pattern recognition within the system. The incorporation of ANN's capacity for complex pattern detection, Decision Trees for optimizing logical sequences, and attention mechanisms for focusing on salient data features offers an innovative and robust foundation for accurate forecasting and efficient management within the system.

Artificial Neural Networks (ANNs) and Decision Trees are pivotal in the management of Smart Solar Systems, particularly in the context of smart cities. ANNs are instrumental in predictive analysis within these systems, effectively forecasting solar energy generation and consumption while supporting load management, energy optimization, and predictive maintenance. ANNs are adept at processing extensive and intricate datasets, recognizing patterns to predict future energy generation and usage, thereby enhancing system efficiency and performance. Decision Trees play a significant role in evaluating and optimizing solar panel configurations, taking into account environmental factors and system parameters. They aid in making decisions regarding the ideal placement and alignment of solar panels, considering variables such as shading, weather conditions, and geographic location. Additionally, Decision Trees are helpful in diagnosing faults, maintaining the system, and predicting its performance under various scenarios. Together, ANNs and Decision Trees are critical in effectively managing smart solar systems within smart cities, contributing to the optimization and sustainability of solar energy utilization in urban environments.

Artificial Neural Networks (ANNs): Artificial Neural Networks (ANNs) are an essential facet of Smart Solar Systems. They are a form of machine learning algorithms designed to mimic the human brain's learning process. ANNs are used to forecast and analyze solar energy production, handle vast datasets, recognize patterns within the data, and make predictions for future energy generation. Their application enables efficient load management, energy optimization, and predictive maintenance, contributing significantly to improving the overall performance and output of solar systems within smart city environments.

Decision Trees : Decision Trees are another crucial tool in managing Smart Solar Systems. They are used to assess and optimize solar panel configurations based on various environmental factors, system parameters, and geographical information. Decision Trees facilitate decision-making processes regarding solar panel placement and alignment, considering factors such as shading, weather conditions, and geographic location. This approach assists in fault diagnosis, predictive system performance, and maintenance planning, thereby contributing to the effective and strategic management of Smart Solar Systems within smart city contexts.

Artificial Neural Networks (ANNs) and Decision Trees are essential elements within the administration and optimization of Smart Solar Systems. Their utilization involves three key stages:

Forecasting and Prediction: ANNs and Decision Trees are crucial in predictive analysis for Smart Solar Systems. ANNs process and analyze extensive datasets, recognizing patterns and enabling precise predictions of solar energy production, consumption, and system performance. Decision Trees contribute to forecasting optimal configurations, considering environmental parameters and specific system attributes, ensuring accurate predictions for ideal solar panel placement, considering shading, weather variations, and geographical influences.

Load Management and Energy Optimization: ANNs in load management within Smart Solar Systems, offering insights into energy requirements and consumption patterns. Decision Trees aid in load optimization by optimizing solar panel settings and configurations, balancing energy generation and consumption to ensure efficient system performance.

Predictive Maintenance and Fault Diagnosis: Both ANNs and Decision Trees play a vital role in predictive maintenance and fault diagnosis within Smart Solar Systems. ANNs facilitate predictive maintenance strategies, forecasting potential system failures or irregularities based on previous patterns and current data. Decision Trees are pivotal in fault diagnosis, identifying irregularities and suggesting corrective measures based on historical and real-time system parameters.

These three stages highlight the integral role that ANNs and Decision Trees play in the administration and optimization of Smart Solar Systems, covering predictive analytics, load management, energy optimization, and maintenance practices. Artificial Neural Networks (ANNs) and Decision Trees represent critical components in the realm of solar systems, particularly in ensuring precision in prediction, effective battery management, and efficient data storage.

3.3 Accuracy and Prediction

ANNs, a class of machine learning algorithms, are pivotal in accurately predicting solar energy generation and consumption within solar systems. These networks process intricate datasets derived from solar panels and other sensors, recognizing significant patterns within the data. Through the analysis of historical solar energy information, ANNs forecast the future energy requirements, thereby facilitating improved load management and more efficient resource utilization. This predictive capability significantly contributes to the enhancement of accurate forecasts of energy production and consumption within smart solar systems.

3.4 Battery Management

In battery management, both ANNs and Decision Trees are instrumental. ANNs assist in forecasting and optimizing battery utilization, contributing to a balanced and optimized charge and discharge cycle. Decision Trees, on the other hand, aid in making strategic decisions associated with battery management, leading to improved longevity and effective use of batteries. Together, these components enhance the efficiency of energy storage systems within solar structures, ensuring sustained and efficient battery performance, crucial to the consistent and reliable operation of smart solar systems.

3.5 Efficient Data Storage

Both ANNs and Decision Trees are valuable in enabling efficient data storage and analysis within solar systems. These technologies support the organization and analysis of the extensive datasets generated by solar panels and accompanying sensors. Their capabilities in data processing and analysis underpin effective decision-making processes and system analyses, which are integral in the context of system maintenance, performance evaluations, and future planning for solar systems. In summary, the application of Artificial Neural Networks (ANNs) and Decision Trees is precise prediction of energy generation and consumption, effective battery management, and organized data storage within solar systems. Their integration creates a robust framework for optimized energy production, efficient battery performance, and meticulous data organization, all of which are vital in enhancing the efficiency and sustainability of solar systems within the infrastructure of smart cities. These technologies significantly contribute to the seamless operation of smart solar systems, facilitating improved energy generation and management within urban settings.

4. Result and Discussion

The comprehensive exploration of current literature has revealed emerging trends in the landscape of smart cities. Focused on establishing cities that are not only habitable but also efficient, the sustainability of smart cities accentuates the pivotal role of a city's infrastructure and its power dynamics. Conversely, this article underscores the significance of Information and Communication Technology (ICT) in effectively amalgamating resources to elevate a city's interconnectedness, intelligence, and overall quality of life. Acknowledging the criticality of technological advancements in shaping smart cities, the article delves into the utilization of diverse technologies, specifically in ensuring the sustainability of these cities, particularly in terms of electricity. It underscores the urgency of research dedicated to exploring the role of smart cities in achieving sustained long-term development. The imperative need for sustainable development in cities is notably highlighted by the emphasis on employing innovative technologies and integrating resources for efficient urban infrastructures, underpinning the interconnectedness and intelligence of smart cities. The piece underscores that the growth of smart cities involves recognizing the importance of city infrastructure and sustainable power generation, urging the adoption and deployment of ICT to better connect resources and enhance overall living standards. The article underscores that technological innovation is crucial in shaping the trajectory of these cities towards sustainability, drawing attention to the varied technological applications that ensure these cities' resilience, particularly in energy management. Additionally, the article stresses the urgency of advancing research dedicated to investigating the indispensable role smart cities play in the sphere of sustained, long-term development. Table 2-4.

This emphasis on technological incorporation serves to pave the way for holistic and efficient smart cities, significantly elevating urban living standards. The research underscores the essential integration of technology and sustainable power resources to nurture cities that are more interconnected and intelligent, serving the goal of comprehensive quality of life enhancements. It ultimately stresses the urgency of establishing a sustained urban development paradigm, underscoring the vitality of in-depth research and sustainable technology for the future success of smart cities.

The article highlights how rapid urbanization prompts the development of "smart cities." Focused on future city development, these cities need to prioritize environmental consciousness. Assessing the sustainability of Australia's major cities, the study evaluates their "smartness." It outlines essential variables and subfactors influencing economic and environmental viability. Governance is the primary factor, followed by land use, environmental management, and retrofitting. The government's role is crucial in realizing smart cities. It emphasizes Australia's sustainable practices in smart cities, serving as models for developing nations.

Comparative evaluation of different models employed in solar power management, (Figure 2) considering key performance metrics. The models, including the Artificial Neural Network (ANN), Support Vector Machine (SVM), Long Short-Term Memory (LSTM), Decision Tree, and Convolutional Neural Network (CNN), are assessed based on their Accuracy, Precision, Recall, F1 Score, Mean Absolute Error/Mean Squared Error (MAE/MSE), Training Time, and Interpretability. The metrics reveal the models' varying effectiveness in capturing and predicting solar power-related patterns. For instance, the ANN exhibits high accuracy and precision but comparatively lower recall, while the Decision Tree model excels in mean absolute error and training time. These insights help in understanding the trade-offs and strengths of each model, aiding in the selection of the most suitable approach for solar power management applications

Table 2 – Comparative Analysis of Machine Learning Algorithms in Solar Energy Smart Sensors: Features and Applications

Algorithm	Key Features	Application in Solar Energy Smart Sensors
Artificial Neural Networks (ANNs)	Analyze complex, nonlinear relationships in data. Process large datasets, predict solar energy production, consumption, and load management.	Accurate forecasting, proactive responses to energy demands, optimization of resource utilization.
Decision Trees	Offer interpretability, aid in decision-making based on environmental factors, optimize solar panel configurations.	Identify the impact of shading, weather changes, and geography on solar energy, fault diagnosis, and system maintenance.
Random Forests	Ensemble learning techniques that aggregate multiple decision trees, reduce overfitting, handle noisy data.	Enhanced prediction accuracy, robustness in prediction, better handling of noise in the data.

Support Vector Machines (SVMs)	Proficient in regression, classification tasks, effective in detecting faults or anomalies.	Detect anomalies in solar systems, classification of energy patterns, suitable for high-dimensional data.

Table 3 – Evolution parameter analysis of AI based solar power management system

Criterion	**Artificial Neural Network (ANN)**	**Support Vector Machine (SVM)**	**Long Short-Term Memory (LSTM)**	**Decision Tree**
Model Type	Neural Network	Supervised Learning	Recurrent Neural Network (RNN)	Tree-based
Complexity	High	Moderate to High	High	Low to Moderate
Interpretability	Low	Moderate	Low	High
Data Requirements	Large amounts of labeled data	Moderate amount of labeled data	Moderate to Large amounts of time-series data	Moderate amount of labeled data
Training Time	Longer	Moderate	Longer	Shorter
Performance	Excellent for complex patterns	Effective for high-dimensional data	Excellent for time-series data	Effective for decision boundaries
Handling Non-Linearity	Effective	Effective	Effective	Inherent capability
Robustness to Noise	Sensitive	Moderate	Robust	Sensitive
Parameter Sensitivity	Numerous hyper parameters to tune	Sensitivity to kernel choice	Numerous hyper parameters to tune	Less sensitive
Applicability	General-purpose, versatile	Well-suited for high-dimensional data	Time-series data, sequential tasks	Simple decision-making tasks
Memory Usage	Depends on architecture	Low to Moderate	Higher	Low

Table 4 - Model Evaluation Metrics for Solar Power Management

Model	**Accuracy**	**Precision**	**Recall**	**F1 Score**	**MAE/MSE**	**Training Time**	**Interpretability**
Artificial Neural Network	0.9	0.8	0.3	0.2	0.223	0.9	0.3
Support Vector Machine	0.8	0.6	0.2	0.1	0.12	0.8	0.2
Long Short-Term Memory	0.7	0.6	0.2	0.1	0.133	0.8	0.1
Decision Tree	0.7	0.6	0.2	0.1	0.01	0.6	0.2
Convolutional Neural Network	0.8	0.7	0.3	0.2	0.11	0.7	0.1

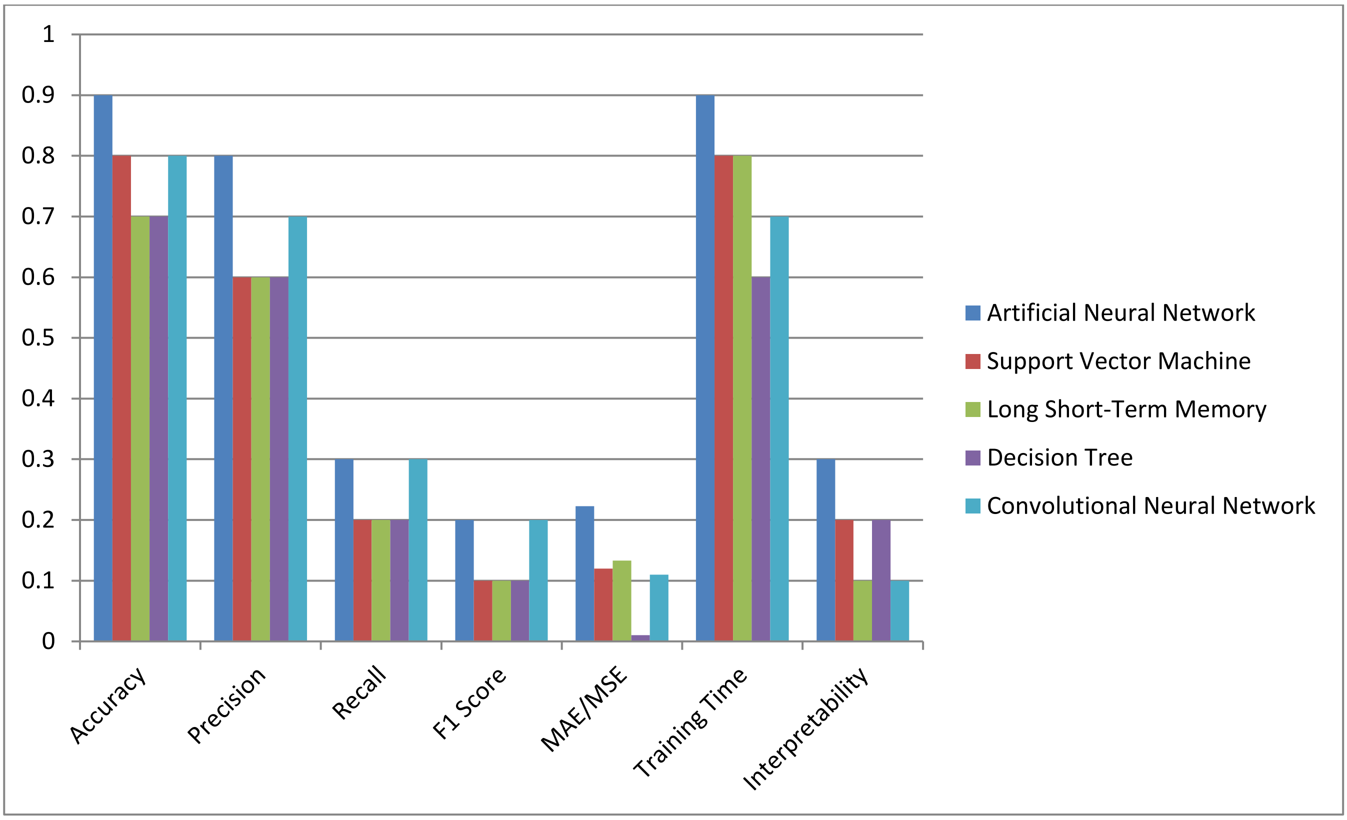

Fig 2- Model Evaluation Metrics for Solar Power Management

5.Conclusion

This research underscores the critical role of data analysis and machine learning in addressing climate change challenges, particularly in optimizing energy consumption within smart cities through solar power systems. Efficiencies in solar irradiance, clear skies, clean panels, and unobstructed sun exposure are highlighted. Integration of sensors and IoT, facilitated by platforms like Arduinos, ensures continuous monitoring of vital parameters in solar panel systems. Focused on Energy Load Forecasting in smart city environments, the study develops and compares a hybrid deep learning model using historical data from a near Zero Energy Building. Tailored machine learning algorithms, including Artificial Neural Networks and Decision-trees, accommodate unique data features like the presence of photovoltaics. A significant contribution is the introduction of a groundbreaking hybrid model, combining outputs from multiple machine learning algorithms into a meta-model voting regressor. This regressor standardizes new data inputs, showcasing the potential to significantly enhance forecasting accuracy. Experimental evaluations consistently reveal the hybrid model's superior performance compared to base algorithms, signifying its effectiveness in predicting energy load in smart city environments. The success of this model not only offers valuable insights but also presents practical applications for advanced machine learning techniques in sustainable urban development, paving the way for further implementation in real-world smart city infrastructures and contributing to a more energy-efficient and environmentally sustainable future.

Author contributions

Author 1 and 2 implemented the concept and drafted the article with assistance of authors 3, 4 and 5, respectively.

Conflicts of interest

The authors declare no conflicts of interest.

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