Artificial Intelligence-based Green Technologies for Efficient Agriculture

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Abstract. Modern agriculture poses an important challenge. It affects food quality, environmental conditions and the agricultural sector's capacity to adapt to climate change. Traditional fertility management methods have significant drawbacks. They sometimes use too many chemicals, lack real-time, location-specific data, and dissipate resources. These problems lead to soil weakening, lower crop yields, and a greater environmental impact. Due to high implementation costs, a lack of Machine Learning model awareness, poor worldwide standards, and variable soil data availability, it is difficult to make data-driven decisions in soil management. This study explores the growing significance in Technologies like Artificial Intelligence (AI) and Machine Learning (ML) in sustainable farming systems by focusing on distant sensing methods, sensor networks with the Internet of Things (IoT), robotics, and data-driven decision support systems. The current state of these technologies and their increasing use in more precise diagnoses and effective soil management are also addressed.

1 Introduction

The quality of soil worldwide has been severely degraded by traditional agricultural methods such as intensive farming, mono-cropping, and excessive use of chemical fertilizers. These practices result in increased erosion, reduced microbial diversity, and decreased fertility, all of which put the long-term viability of agriculture at risk. On the other hand, intelligent, green soil methods powered by advanced technologies like Machine Learning (ML) and Artificial Intelligence (AI) which provide a promising step toward sustainable soil management. These technologies provide real-time, data-driven solutions that enable precise and adaptable interventions to protect soil health.

The combination of sensors, drones, satellite and internet of things (IOT) which are based on the remote sensing systems with continuous monitoring of key soil features, such as moisture content, pH, and nutrient levels, across various locations and periods. Advanced ML [1] approaches, such as convolutional neural networks (CNNs) and transformer-based models, are used to analyze multimodal datasets to predict erosion-prone areas, soil fertility, and nutrient deficiencies. Notable applications include mobile colorimetric pH mapping systems with high accuracy and edge-cloud Artificial Intelligence platforms, which enable precise irrigation methods and result in reductions in water usage.

In addition, the combination of sustainable cultivated practices, such as zero tillage, crop rotation, cover cropping, and composting utilization, with Artificial Intelligence-driven diagnostics improves soil structure and microbial activity. Furthermore, innovative solutions like Nano fertilizers and bio-char-enhanced soil amendments are emerging, offering targeted nutrient delivery and effective pollution cleanup with little environmental impact.

The major categories into which this study divides green soil technologies are as follows: Precision diagnostics and AI-enabled irrigation, Conservation cultivation and regenerative field techniques, Organic amendments and microbial enhancement, Nano-enabled nutrient management, and smart monitoring systems that combine IoT, ML, and remote sensing. In order to demonstrate AI inclusion throughout the soil management process, a visual framework is provided that extends from monitoring and analysis to precise action. AI is extremely essential in increasing crop output, so the farmers may plan the crops depending on soil quality by taking into account PH, fertility, and moisture content of the soil.

In Figure 1, a centralized framework is shown. “Applications of AI in Precision Agriculture”, [1] are divided into five branches, each representing a specialized application area:

1. Crop and Soil Monitoring: AI algorithms examine sensor data and satellite image to measure soil health, moisture levels and crop growth patterns in real time.
2. Crop Disease Detection, Pest Control and Management: Machine learning models identify early signs of disease and pest infestations, enabling timely involvement and minimizing yield loss.
3. Weed Detection and Management: Machine Learning systems distinguish weeds from crops,

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facilitating targeted application and reducing chemical usage.

4. Resource Management: AI optimizes the use of water, fertilizers and energy by predicting needs and automating distribution, enhancing sustainability.
5. Supply Chain Optimization: Predictive analytics and intelligent logistics improves harvest, storage and reducing waste and improving market efficiency.

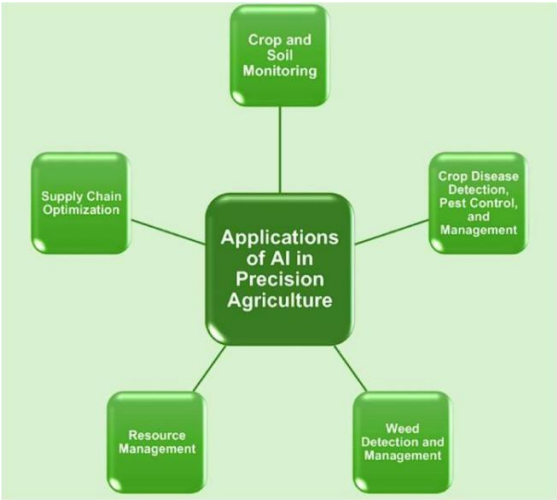

Fig. 1. Centralized framework of application of AI in precision agriculture [1].

This survey examines cutting-edge technology, such as federated learning for privacy-focused soil diagnostics, drone-based erosion modelling, and edge computing solutions for remote decision-making, by looking at improvements in sensor network architectures, intelligent control systems, scalable farming models, and field applications. Additionally, it examines existing constraints and gaps in technology, ecology, and socioeconomics. This objectives provide a clear idea for scientists and agronomists, which focuses on implementation obstacles, data standardization challenges, model interpretability issues, and the need for scalable deployment methods across a variety of agricultural systems.

2 Literature Survey

2.1 Soil Fertility Assessment and Crop Recommendation Using Machine Learning.

A Machine Learning model is used for predicting soil fertility for relevant crops was introduced by R. Mynavathi. The model focuses on soil characteristics like nitrogen (N), phosphorus (P), potassium (K), [1] temperature, pH levels, and rainfall in order to make the best data-driven recommendations. One of the system's most notable features promotes sustainable agriculture by allowing organic enrichment of the soil through the recycling of crop leftovers. The study uses cloud integration and mobile platforms to aid precision agriculture in rural regions, but it does not explore multimodal Artificial Intelligence integration, such as combining remote sensing with sensor fusion for comprehensive soil monitoring.

2.2 Crop Analysis and Classification Using Machine Learning Based on Soil and Environmental Characteristics

B. M.G. S and T. Rao [2], proposed a Machine Learning model for selecting and categorizing crops based on a variety of soil and environmental parameters. Their research demonstrates how support vector machines and decision tree-based algorithms can aid in adaptable crop planning in uncertain circumstances. The approach enhances yield prediction and resource efficiency through the principles of precision agriculture. The study, though, focuses only on crop categorization tasks; it excludes real-time sensing, automated systems, and methods designed to manage soil in an environmentally conscious manner.

2.1 Agri-Nexus: An IoT-Driven Autonomous Ecosystem for Smart Agriculture

S. Pitta introduces Agri-Nexus, an automated farming platform that uses Blockchain, Artificial Intelligence, the Internet of Things, and edge computing [3]. All these system allows for simultaneous resource allocation, drone-based pest control, and dynamic decision-making through self-learning models. Agri-Nexus encourages ecologically friendly approaches and aids in lowering pesticide use. Although the study is thorough, it primarily focuses on automating the entire farm and pest management, as opposed to paying close attention to thorough soil diagnostics and regenerative soil health models that are supported by Deep Learning or transformer-based strategies.

2.2 An Intelligent and Cost-Effective IoT-Based Irrigation System Using Machine Learning.

Using a variety of IoT sensors to observer soil moisture, water levels and other environmental parameters, S. Kadiyala developed an inexpensive smart irrigation system in the study [4]. For predictive irrigation control, the study employed Machine Learning techniques such as Decision Trees, Naive and Artificial Neural Networks (ANN). These driven rovers provide continuous operation while protecting crops and preserving the environment.

2.3 Crop Recommendation System using Random Forest Algorithm in Machine Learning

This work will discuss the crop recommendation system created by S. R. Sani, S [5], which uses Machine Learning approaches. Crop advice is essential for promoting sustainable agricultural practices and boosting crop yields. Which will provide the best crop for the environment, taking into account a variety of variables such as phosphorus (P), potassium (K), and humidity. This will investigate a number of algorithms, including KNN, Decision Tree, Random Forest, SVM,

etc., but will choose the random forest method because it has varying degrees of accuracy. In this paper, a crop recommendation system using the random forest technique is presented. The model's precision will be evaluated using an accuracy score, and a large dataset will be used to train it. Ultimately, the trained model is used to predict the ideal crop for the area based on the specified criteria. This will enable decision-makers, academics, and farmers to make well-informed choices about crop management and planning.

3 The Benefits of Using Artificial Intelligence in Agriculture

The study of energy-efficient, environmentally friendly Machine Learning methods and intelligent systems is known as Green Artificial Intelligence (AI). It is essential to contemporary farming. This can significantly enhance production, environmental sustainability, and environmental care by integrating Green Artificial intelligence into intelligent agriculture systems. Green AI [6], has particular benefits when used in key agricultural techniques such as irrigation drones, security rover robots, planting bots, robot sprinklers, automated tractors, and field sensors, which illustrates the architecture of an Artificial Intelligence-assisted farm.

In the Figure 2, shows Smart Farming in different domains of agriculture. The domains are:

1. Security Rover Bot: A mobile robotic unit furnished with sensors or cameras, used for real-time monitoring this enhances security, detects intrusions and can also track animal movement or status.
2. Irrigation Drone: drone system planned to automate crop irrigation. It enables targeted water delivery based on crop needs, reducing water waste and improving hydration efficiency across large fields.
3. Planting Bot: A robotic or autonomous machine responsible for sowing seeds with precision. It ensures uniform planting depth and spacing.
4. Field Sensor: Ground-based sensors that collect environmental data such as soil moisture, temperature, pH, and nutrient levels. These sensors support real-time decision-making for irrigation, fertilization and crop health management.
5. Autonomous Tractor: A driverless tractor capable of performing tasks like ploughing, planting, and harvesting. It operates using GPS, AI algorithms and sensor data, reducing human intervention and increasing operational efficiency.
6. Robot Sprinkler: A smart irrigation system that uses robotics to deliver water precisely where needed. It adapts to crop type, growth stage, and weather conditions, promoting water conservation and optimal crop hydration [6].

This Figure 2 encapsulates the essence of Smart Farming a data-centric, automated approach to agriculture that enhance productivity, reduce resource consumption and support sustainable practices

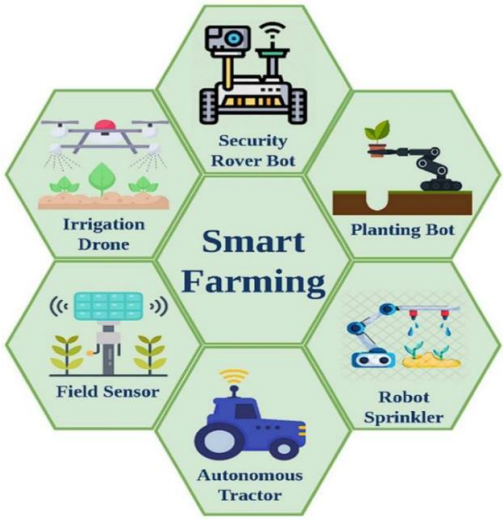

Fig. 2. Represents a hexagon-based smart farming [6].

3.1 Precision Irrigation with AI-Powered Drones

With the use of multispectral imaging and real-time sensor data, Green AI delivers water precisely where it is needed, minimizing excessive distribution [6]. This targeted strategy promotes more sustainable agricultural techniques and helps to conserve a lot of water. Additionally, lightweight Artificial Intelligence systems boost energy efficiency, allowing drones to operate longer on a single charge, which reduces the environmental impact of irrigation projects.

3.2 Energy-Efficient Security Rover Robots for Crop Protection

Security rover robots, when coupled with Green AI, provide round-the-clock surveillance of agricultural lands while using the least amount of energy. Edge computing is used for real-time threat analysis, such as animal invasions or pest infestations, which reduces reliance on energy-intensive cloud services. When powered by renewable energy sources like solar panels, these AI-driven rovers ensure continuous operation while maintaining environmental equilibrium and crop security.

3.3 Planting that is optimized via autonomous planting bots

Planting bots use Green AI technology to evaluate the soil composition and humidity levels in order to determine the most effective seed placement. This precise planting method improves crop yield, conserves resources, and reduces fuel consumption through optimal path planning. By limiting unnecessary soil disruption, these robots also help to maintain the health and natural structure of agricultural land, hence promoting long-term sustainability [7].

3.4 Smart Water and Nutrient Management using Robotic Sprinklers

By using water and fertilizers only in specific locations that require treatment, robot sprinklers take advantage of Green AI based on real-time analysis. This encourages environmentally friendly farming, reduces input excess, and prevents chemical runoff. Furthermore, AI algorithms schedule watering during the optimal conditions, cooler hours to minimize evaporation losses, hence promoting the efficient use of water and energy resources.

3.5 Green AI-powered field sensors

Provide real-time data about crucial soil properties such as moisture content, nutrient content, and pH balance [8]. These sensors employ low-power, on-device processing to cut down on energy usage and transmission overhead. When utilized with solar energy, they offer scalable, environmentally friendly solutions for high-accuracy agriculture, enabling farmers to make wise decisions that improve productivity while protecting the environment.

4 Machine Learning in Agriculture

Machine Learning algorithms like Random Forest help in predicting soil fertility, Nutrients [9], Moisture, and PH. Considering the scenario of the Random Forest algorithm to predict soil fertility based on nutrients (NPK), moisture, and pH.

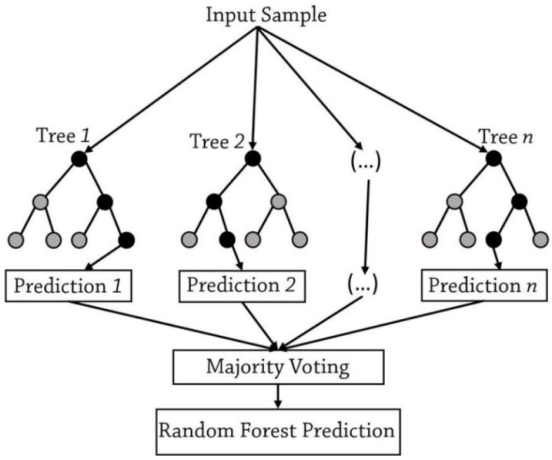

Fig. 3. Mechanism of random forest methodology [8].

In the Figure 3, the illustration of the core mechanism of the Random Forest algorithm, is given, it visually represents how multiple decision trees collaborate to produce a robust and accurate prediction.

1. Input Sample- A data instance is fed into the Random Forest model for classification or regression.
2. Multiple Decision Trees (Tree 1 to Tree n) - The input is simultaneously passed through several independently trained decision trees. Each tree has learned patterns from different subsets of the training data, often with randomized features to ensure diversity.
3. Individual Predictions (Prediction 1 to Prediction n) - Each tree generates its own prediction based on the input sample. These predictions may vary due to the trees' unique training paths.
4. Majority Voting (for Classification) - The individual predictions are aggregated using a majority voting scheme. The class label that receives the most votes becomes the final output.
5. Final Output: Random Forest Prediction - The ensemble decision, derived from the collective intelligence of all trees, is returned as the model's prediction [8]. This approach improves generalization compared to a single decision tree.

```
DATASET
data = {
    'Nitrogen': (0, 100, 100),
    'Phosphorus': (0, 100, 100),
    'Potassium': (0, 100, 100),
    'Moisture': (10, 40, 100),
    'pH': (5.5, 8.5, 100),
    'Fertility': np.random.choice(['Low', 'Medium', 'High'], 100)
}
Encode target labels
df['Fertility'] = df['Fertility'].map({'Low': 0, 'Medium': 1, 'High': 2})
Features and target
X = df[['Nitrogen', 'Phosphorus', 'Potassium', 'Moisture', 'pH']]
y = df['Fertility']
    Random Forest model [5]
model = RandomForestClassifier(n_estimators=100, random_state=42)
model.fit(X_train, y_train)

Predictions and evaluation
y_pred = model.predict(X_test)
print("Accuracy:", accuracy_score(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

4.1 Applications of Artificial Intelligence in Agriculture

By using Artificial Intelligence revolutionization in agriculture, improving irrigation and farming, and by choosing the harvest time. It may identify nutrient deficits, detect diseases, and manage pests.

The assessment of intelligent soil technologies that maximize nutrient cycles, reduce chemical inputs, and increase carbon sequestration is a comprehensive taxonomy of AI/ML uses in crop and soil management [10].

Furthermore, emphasizing their ecological effects and practical uses in the real world.

4.1.1 Forecasting agricultural output

To estimate crop yields, Random Forest [11], makes use of historical data such as soil properties, climatic variables (temperature, humidity, fertilizer usage, crop

type, and planting dates). Other methods, such as SVM and neural networks, are often more accurate in terms of forecast accuracy.

4.1.2 Select the characteristics

Aids in determining the key variables influencing crop production, enhances model performance, and decreases computer complexity.

4.1.3 Assistance for farmers' decision making

Random Forest models [12], may be used in web applications to predict the output of specific crops and recommend appropriate fertilizers and crops for particular situations, effectively managing intricate, nonlinear relationships between variables.

Particularly resistant when dealing with data from the agricultural sector, which is common in precision farming, it is capable of managing massive datasets with many features.

4.1.4 Implications for the real world

By optimizing resource utilization and minimizing environmental impact, sustainable agriculture helps farmers make informed choices, reduce risk, and improve productivity.

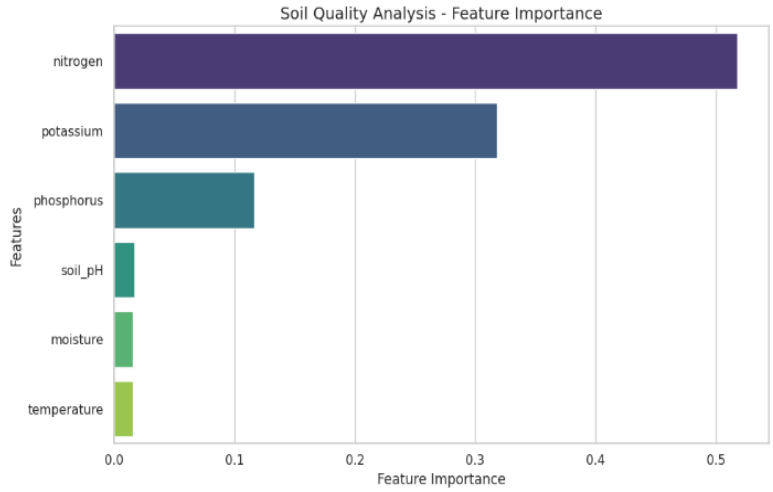

Fig. 4. Graph representing soil quality analysis [13].

In the Figure 4, graph shows how different soil attributes contribute to overall soil quality, based on a machine learning model's feature. The x-axis represents Feature Importance how influential each feature is in predicting soil quality, while the y-axis lists the Features being evaluated.

1. Nitrogen

The most critical factor in determining soil quality. Essential for plant growth, chlorophyll production, and overall crop yield.

2. Potassium

Second most influential, Vital for water regulation, enzyme activation and disease resistance in plants.

3. Phosphorus

Supports root development and energy transfer.

Plays a key role in early plant growth and flowering.

4. Soil pH

Moderately important, Influences nutrient availability and microbial activity in the soil.

5. Moisture

Slightly less impactful in this model.

Affects nutrient transport and root function, though its importance may vary seasonally.

6. Temperature

Least influential in this context.

While it affects microbial processes and plant metabolism, it may be less variable or less predictive in the dataset used [13].

The use of Artificial Intelligence (AI) in agriculture has increased significantly between 2020 and 2025. This growth is being driven by the need for precision farming, environmentally sustainable practices, and data-driven decision-making. According to various market reports, the market for AI in agriculture is expected to reach about a billion by 2025[14]. This represents a compound annual growth rate. This increase points to more investment in agro-tech innovation from the public and private sectors. This expansion is highlighted by key performance indicators. One indicator is the rate at which AI-enabled devices are adopted, such as field sensors [15], automated drones, robotic sprayers, and AI-based crop monitoring platforms. The rate of adoption among medium to big farms is more Smallholder farms also made progress due to inexpensive and energy-efficient designs. Additionally, over this time, the accuracy of AI-based crop yield forecasts has increased due to improved datasets.

The efficiency of resource utilization is another important consideration. Green Artificial Intelligence models that focus on environmental and energy issues were used in intelligent irrigation systems to help conserve water. On AI-assisted farms, fertilizer usage was reduced by almost half thanks to improved soil analysis and application schedules. These results not only cut costs but also promote sustainable agriculture by reducing runoff and ecological harm.

Increased agricultural productivity was another feature of the time. Early detection success rates have significantly increased thanks to AI-driven pest and disease detection models, resulting in a large reduction in crop losses. AI-powered autonomous tractors and planting robots have increased the efficiency of field operations, lowering labor expenses and operating time. Improved decision-support systems improved the efficiency of logistics and postharvest procedures. Overall, between 2020 and 2025[8], the usage of AI in agriculture went from experimental stages to widespread use. The enormous potential of Artificial Intelligence technologies is demonstrated by the expanding market and improved performance indicators. Continuous innovation, infrastructure investments, and regulatory assistance should all contribute to increasing the role that Artificial Intelligence plays in promoting sustainable agriculture and global food security.

4.2 The advantages of using the random forest algorithm

A number of Artificial Intelligence methods, such as Machine Learning algorithms, Deep Learning algorithms, computer vision algorithms, natural language processing (NLP), reinforcement learning, decision tree algorithms, and support vector machines, are used in many sectors of agriculture. For example, the soil quality is assessed using the Random Forest technique.

The Random Forest approach is ideal for data that is tabular and limited, such as soil moisture, pH, and nutrients. It is extremely understandable and useful for identifying significant soil indicators through feature importance. It provides rapid training and consistent performance for soil moisture prediction, especially in short-term forecasting scenarios.

This method is used in agriculture for yield prediction, soil classification, crop categorization, and crop disease identification, all of which are typical Machine Learning applications.

Creating a inclusive taxonomy of the uses of Artificial Intelligence/Machine Learning in soil and crop management, is the assessment of smart soil technologies that increase nutrient cycles, reduce chemical inputs, and enhance carbon sequestration.

5 Comparative analysis

In the Table 1, a side-by-side comparison of key agricultural dimensions, highlighting how Artificial Intelligence (AI) and related technologies are revolutionizing farming practices are shown [16]. Each row contrasts conventional methods with modern, data-driven approaches.

Compared to traditional methods, from Table 1 AI-based approach offers higher input efficiency, better yield predictability and significantly lower environmental impact and Decision-making shifts from manual to automated, enabling smarter and more sustainable farming.

Table 1. Modern AI-powered farming versus conventional farming practices [16].

Aspect	Traditional Farming	Modern AI-Powered Farming
Decision Making	Depends on experience, intuition, and fixed schedules	Data-driven, uses real-time AI-based decision support systems
Resource Utilization	More wastage of water, fertilizers, and pesticides	Optimized use via IoT sensors and drones.
Crop Monitoring	Manual inspection is time-consuming and error-prone	Automated with drones, satellite imagery, and AI for real-time tracking
Yield Prediction	Estimated through seasonal trends and experience	Accurately predicted using ML models analyzing weather, soil, and crop data.
Labor Dependency	Labor-intensive, physically demanding	Automated tasks using robotics and autonomous systems
Cost Effectiveness	Higher operative costs due to inadequacies	Lower charges due to predictive maintenance and optimized inputs
Scalability	Difficult to scale without more land or labor	Easily scalable through cloud-based systems and smart farming tools
Environmental Impact	Often leads to soil degradation, overuse of chemicals	Supports sustainable practices with minimal ecological impact

6 Conclusion

In agricultural soil management, the combination of Artificial Intelligence (AI) and green technology provides an opportunity to solve enduring issues in the field. This study looked at how robotic systems, field sensors, self-propelled tractors, and smart irrigation drones will help to improve the precision, efficiency, and sustainability of soil monitoring and resource management. These AI-driven technologies offer superior diagnostics, less chemical usage, and more accurate crop yield forecasting when compared to conventional methods, all while reducing environmental harm. This integration is caused by cost fusion, a lack of digital infrastructure in rural areas, a lack of farmer awareness, and the need for transparent and compatible Artificial Intelligence algorithms. Addressing these challenges necessitates policy support, cooperative research, and investment in rural education and connectivity.

The future of AI-based soil management depends on the development of simpler AI models, low-power Green AI algorithms, and open-access agricultural datasets that benefit both large farms and smallholders. Furthermore, the use of Blockchain for Secure data sharing and edge computing for real-time field processing supports decentralized and sustainable agricultural systems. Collaboration between agronomists, AI researchers, legislators, and local organizations is essential to making sure that these smart solutions are not only technically sound but also economically viable and socially inclusive.

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