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Dependency of the learning technique on the problem nature

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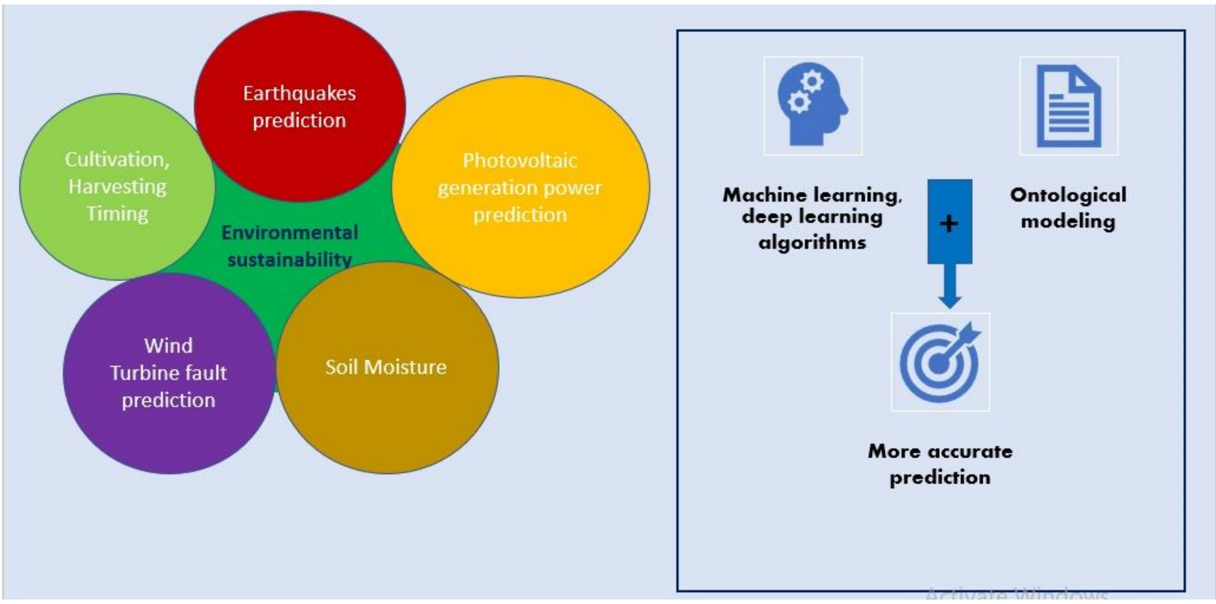
ABSTRACT

Indicators perception and prediction based on available datasets have recently gained increasing importance. Artificial intelligence (AI) is the backbone of perception and prediction; learning techniques are being used by most researchers to achieve these goals while ontologies are being used to collect, represent, understand and use input data. Using a comprehensive ontology can improve the process of incrementally learning a visual concept detection model. The problem nature may be in healthcare, Transportation, etc. Applying AI to different environmental sectors like solar irradiation, agriculture, water domain and other natural disasters has increased in recent years due to weather changes and human activities. Achieving high accuracy and high efficiency have always been challenges for researchers for faster natural disaster management or natural phenomena exploitation in economic development. With inflating data, there is a direction to deep learning models and hydride methods that enhance the outcome. This paper reviews how artificial intelligence applied in different environmental applications and the development stages of AI models until now. It shows the advantages and disadvantages of each model and provides appropriate recommendations for each application to achieve the best forecasting.

Graphical abstract



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1. Introduction

According to a recent massive database, artificial intelligence (AI) models become more reliable than other models in processing, interpretation, and prediction [1]. With developing technology, a lot of natural problems are increasing every day. Nature problems may be represented in environmental aspects, transportation [2], healthcare [3], etc. Environmental problems have been more attention to most researchers recently. With weather changes and human activities [4], there are more problems in agriculture [5], lack of water [6], photovoltaic power generation [7], and others. On the other hand, there are natural disasters like earthquakes, flooding, and others [8].

To avoid the consequences of these problems, AI models have been applied in different environmental fields to predict. In the past few years, deep learning models applied in most prediction application parallel with increasing data.

Studies have found that up to 85% of AI projects fail [9]. This is mainly explained by a lack of comprehension of how to use a massive amount of data. Ontological modeling may help an AI system by expanding its scope. Ontology can contain any type of (structured, semi-structured, unstructured) data format means that it can connect and qualify data without being necessary to normalize them [10]. So, it can address any massive data as input. Ontologies may also contribute to improved data quality in training datasets. An ontological data model may also be used for creating a knowledge graph [11].

This paper shows some environmental applications and the AI models are used in every application. It represents why this model is used in this application.

2. Artificial intelligence

The idea of artificial intelligence is found on the hypothesis that the process of human thought can be mechanized which can be traced back to ancient Indian, Chinese, and Greek philosophers [12]. AI can integrate math, computer science, psychology, philosophy, cybernetics, and other advanced fields. In the next few years, the intelligent machine will replace human abilities in many fields [8]. Artificial intelligence is consisting of three main sequence steps; perceiving, analyzing, and reacting. These steps are combined into one term called intelligence [13]. Climate change is an urgent problem for researchers around the world, and applying AI may help in saving our environment. Accordingly, to the developing internet of things and big data technologies, AI become the more suitable system for interpreting any external data and also learning from other data [4]. Machine learning algorithms can find important patterns in data that help detect the target. Recently, deep learning models are the most used to predict environmental spot trends because of increasing data rapidly. Neural networks-based deep learning has successfully addressed multiple complex applications such as images, videos, translation, text analysis, and other complex problems [14].

2.1. Machine Learning

Models of machine learning are considered as the output of training datasets that used the target function to link between inputs and outputs. The task that the user wants is detecting types of machine learning models to use such as classification, regression, reduction, clustering, deep learning, etc [15].

2.1.1. Classification models

Classification is responsible for expecting the sort of object inside a limited number of options. The output of classification models is explicit. Some significant models are noted in the following [16]:

a. SVM (support vector machine): utilized for binary or multi-class classification [17].
b. Naive Bayes: depend on naïve theorem.
c. Decision Tree: more reliable for outliers.
d. K-Nearest neighbors: basic however computationally thorough.
e. Ensembles: Mix of numerous ML models clubbed together to improve results.

2.1.2. Regression

Learning regression is a bunch of issues where the result variable can take consistent qualities. Some significant models are noted in the following [16].

a. Linear regression: functions admirably just when information is directly distinguishable and extremely less or no multicollinearity is available.
b. Ridge regression: works as linear regression with L1 regularization.
c. Lasso regression: works as linear regression with L2 regularization.
d. Support vector regression, decision tree regression, etc.

2.1.3. Clustering

Clustering is the assignment of collecting comparative objects together. It assists with distinguishing comparable objects consequently without manual mediation in a smarter way. Some significant models are noted in the following [16].

a. K means clustering: Simple model but suffers from high variance.
b. K means++: a modified model of K means clustering.
c. K medoids, Agglomerative clustering, density-based clustering algorithm, etc.

2.1.4. Dimensionality Reduction

Dimensionality is the number of indicator factors used to predict the free factor or target. In reality datasets, the number of factors is excessively high. An excessive number of factors likewise bring the scourge of overfitting to the models. Practically speaking, among these huge quantities of factors, not all factors contribute similarly towards the objective, and in an enormous number of cases, we can protect differences with a lesser number of factors. Some significant models are noted in the following [16].

a. SVD (Singular value decomposition): break down the matrix into more modest parts to effectively work out.
b. TSNE, PCA, etc.

2.1.5. Deep Learning

Deep learning is the branch of machine learning that depend on neural networks. Today the use of DL has become fundamental because of their knowledge, productive learning, exactness, and strength in the model structure. Deep learning strategies are quickly developing for better execution. Writing remembers sufficient survey papers for the advancing calculations specifically application spaces like renewable energy prediction, 3D detected information characterization, sight and sound investigation, opinion grouping, text discovery, transportation frameworks, action acknowledgment in radar, hyperspectral, clinical ultrasound examination, picture cytometry, and Apache flash. Some significant models are noted in the following [18].

a. CNN (Convolutional Neural Network): CNN is quite possibly the most known structure of DL strategy. This procedure is for the most part utilized for image processing applications. CNN contains three kinds of layers with various convolutional, pooling, and completely associated layers. CNN is applied in many applications like condition monitoring of wind turbines [19], Prediction of aerodynamic flow [20], motion estimation and correction of medical imaging [21], advanced image processing [22], and crop yield prediction [23].
b. RNN (Recurrent Neural Networks): RNN is intended to perceive successions and examples like text, handwriting, and other applications. RNN is essentially a standard neural network that has been stretched out across time by having edges which feed into the following time venture rather than into the following layer in a similar time step. Every one of the past input data is kept in a state vector in hidden units, and these state vectors are used to register the result. Some applications applied RNN like wind speed prediction [24], tropical cyclone intensity prediction [25], stock price trends prediction [26], music genre recognition [27], ship trajectory restoration [28], and other applications.
c. Long Short-Term Memory (LSTM): LSTM is an RNN technique that benefits input associations and with is utilized as a broadly useful PC. This strategy can be utilized in pattern recognition and image processing applications. There are three central units; input, forget gates, and output. One of the primary strengths of the LSTM technique is that it decides every one of these given the current input itself. Some applications applied based on LSTM like Time Series Prediction, Structural seismic prediction [29], Earthquake trend prediction [30], Wind turbine power prediction [31], Air quality prediction [32], Solar radiation forecasting [33], Volatility forecasting [34], Fault prognosis of battery systems [35] and other applications.

Deep learning techniques are quickly advancing. Some of them have been progressed to be accomplished in a specific application space.

3. Ontology in AI

In Ontology is a concept of being in philosophy study and information science, ontology is a set of objects and attributes in a specific domain that describe the relationship between them. An ontology is an explicit specification of a conceptualization of a domain. i.e., it is used to determine expected significance through the knowledge domain. The power of AI is represented in domain knowledge as input to any model to constrain search and achieve better solutions faster. In the field of life sciences, ontologies are used to encode domain-specific knowledge for annotation. Axioms, definitions, natural language labels, and other types have represented the forms of encoding. Also, reusing domain knowledge can be allowed in ontologies. Well-defined ontologies can be merged to build complex and large ontologies. So, Ontology is considered an important aspect of Artificial intelligence. It has an important role in increasing the accuracy of the prediction [36].

4. Importance of applying AI in Environmental science

SequencThe history of AI in environmental science throughout the most recent forty years has been driven by a fast advancement of earth perceptions, interchanges data transfer capacity, figure abilities, and AI Methodologies. Applying AI to certifiable issues has become more critical as the adverse consequences of climate occasions have become worldwide with an evolving environment, developing populaces in weak regions, and proceeding with impractical practices. Man-made intelligence has entered the social standard as web-based media, diversion, and retail ventures have seen organizations, like Google, Amazon, and Facebook, based on creative AI which become the most important on the planet.

Those organizations, as well as scholarly analysts, have created better ML techniques and an undeniably full-grown arrangement of programming instruments, work processes, and best practices. Confronted with a volume and speed of ecological data a long way past the capacity of people alone to make due, environmental science experts have normally gone to computerization injected with AI and ML to determine new information and give constant noteworthy expectations, expanding the abilities of specialists and forecasters to support society. While early exercises of the American Meteorological Society AI Committee included many zeroed in building information bases and master frameworks to encode and computerize the points of view of human specialists, the coming of progressively hearty, quick, and logical ML strategies - - including DL - - has caused an unavoidable change toward utilizing ML techniques. While master information stays fundamental to suitably forming the learning issue, including the information and "elements" (amounts got from the crude information) given as information and the learning evenhanded, these techniques are allowed to find and take advantage of connections not recently known or effectively expressed. Accordingly, after some time, the direction of AMS AI Committee gatherings has been progressively data-driven.

Whenever AI started being applied to the atmospheric sciences, it was for research purposes and not so much for functional use. To progress to tasks, AI should demonstrate dependability. Forecasters are now barraged with data and won't focus on extra information on the off chance that they don't confide in it. Part of the objective of XAI (explainable AI) is to further develop trust by logical end-clients by giving them a superior comprehension of how a model produces its expectations. Also, information on the situations in which the model will in general progress admirably or inadequately empowers the client to all the more certainly adjust their trust in the model expectations in individual cases. Concentrating on trust from the sociology perspective is likewise basic as it is vital to comprehend the reason why different end clients will pick various wellsprings of data and how can be further developed confidence in AI [37].

5. Recent environmental applications

Climate change is an urgent issue for researchers, so they try to make a positive environment by applying AI models. AI can predict the best time for harvesting and cultivation, Photovoltaic generation power, earthquake locations, times of flooding, etc. (Table 1).

Table 1. Description of some ai applications.

Nature zone	Prepared data	ML methods	Application	Evaluation Indicators
Australia Solar Centre [38]	HQC ontology	GRU recurrent neural network -LSTM	Photovoltaic generation power prediction 2021	Load and reasoning time MSE
Ashmoun, El Menoufia city, Egypt [39]	Crop ontology to generate a recommendation system	SVM	Cultivation and harvesting timing 2020	MAE
the Tsinghua University campus, China [40]	Time-frequency distribution (TFD)	CNN	A deep learning approach to rapid regional post-event	The consumed time by the CNN models and the NLTHA are compared
Ridgecrest in southern California [41]	FMNet with the synthetic data	Focal Mechanism Network (FMNet)	Real-time determination of earthquake focal mechanism via deep learning 2021	MSE
China [42]	high-resolution remote sensing images and a digital elevation model (DEM)	stacked autoencoder (SAE)	Accurate Prediction of Earthquake-Induced Landslides Based on Deep Learning Considering Landslide Source Area 2021	overall accuracy (OA), Precision, and Recall
Japan [43]	representing data as a sequence of heat maps	CNN-RNN(LSTM)	Recurrent Convolutional Neural Networks help to predict the location of earthquakes in 2020	PR AUC and ROC AUC
in Calgary, Canada [44]	Land Use Change Ontology (LUCO)	RNN	Land Use Change Ontology and Traffic Prediction through Recurrent Neural Networks 2021	RMSE
wind farm in Yunnan [45]	SNN ontology	CNN-LSTM	Wind turbine fault prediction 2021	accuracy
The Australian Murray Darling Basin [46]	MODIS Satellite dataset from NASA	CEEMDAN-CNN-GRU(LSTM)	Soil Moisture 2021	
The Urmia Lake water, Iran [47]		adaptive neuro-fuzzy inference system (ANFIS) and multilayer perceptron (MLP) models are hybridized with a sunflower optimization (SO) algorithm {ANFIS-SO}	Lakewater level prediction and uncertainty analysis 2021	RMSE

5.1. Photovoltaic generation power

Solar energy has the attention of individuals because it is clean and renewable energy. Decreasing the prices of photovoltaic cell encourage people to build them. But meteorological factors impact these cells like solar irradiation intensity and other factors that may make a series of problems [48]. Table 2 shows previous predictive methods and their results.

Table 2. Comparison between ml methods.

Ref.	Result	Disadvantages	ML methods
Mohamed et al [49]	Random forest and additional tree algorithms	Predict for the following hours	Fail to predict for a long time
Giorgi [50]	Multiple linear regression	Predict	Poor accuracy
Shan et al [51]	Back propagation-SVM-ELM and SOM-LSF	verified only microgrid	Fail in large-scale photovoltaic power station

To get a better forecast rate, it is important to collect more accurate environmental data. Ontology can collect accurate data by improving the quality of context and thus achieve high accuracy in prediction.

In 2021, Liu et al uses 3Lconont ontology to evaluate HQC (high-quality context) Ontology. To solve the problem of long sequence data, GRU (gated recurrent unit neural network) model is used by adding memory cells which gives more accurate results and speed prediction [38].

5.2. Forecasting in agriculture

Agriculture is one of the most pivotal fields contributing to the improvement of any country where it affects on economies of nations. Achieving optimum cultivation and harvesting times have been a challenge for farmers according to environmental conditions like water, climate, and soil. Machine learning (ML) techniques can predict planting and harvesting times. Table 3 shows various types of crops and ML techniques [52].

Table 3. ML techniques for various application

Ref.	Crop type	ML technique
Fourie et.al. [53]	Orchard	CNN
Cheng et al. [54]	Apple	BPNN
Villanueva and Selenga [55]	Bitter gourd	CNN
Oliveira et al. [56]	Maize, soybean	RNN
Chlingaryan et al. [57]	Common bean, wheat, soya bean	SVM, SVR, BG, REP tree
Osman et al. [39]	Tomato	SVM+ crop ontology

Fourie et al. proposed a method to predict an automated system of crop yield through periods of growth. CNN (Convolutional neural network) was used to detect images that contain fruits, branches, or other parts of the orchard [53].

Cheng et al. proposed a new method to early predict the crop of fruits (apples). BPNN (back propagation neural network) technique is applied by using image analysis means. This technique was established in two stages of the season (the opening stage, and the maturity stage) [54].

Villanueva and Selenga use a Convolutional neural network (CNN) to predict the natural product-bearing capacity of bitter ground in Batangas City, Philippines. This study showed checking the healthy leaves of plants based on color and shape. If the leaves are yellow or brown and in small size, these leaves would not be significant to bad leaves whereas leaves in normal size and green are good leaves. This prediction was achieved from at least 239 images. Keras, python, and tensor flow worked to gather training data [55]. Oliveira et al. use RNN (recurrent neural network) to predict pre-season yield and this enables farmers to decide to detect different crops before seeds occur. In this study, RNNs can detect redundant information about metrological data and soil to obtain scalable yield forecasts [56].

Chlingaryan et al. reviewed various machine learning models to early predict many crops yield in the last 15 years before 2018. This review showed good solutions in the prediction that easily estimate crops and better make decisions [57]. Osman et al. proposed a different approach: 1. Applied SVM (support vector machine) model in prediction and calculating GDD. 2. Build ontology from the database and accumulative GDD. 3. Evaluate crop ontology from a reasoner that gives a better recommendation to the farmers to decide on the cultivation and harvesting times of tomato crops [39].

5.3. Machine Learning

Earthquakes are one of the most hazardous natural phenomena. They occur without previous warning. Forecasting earthquakes are the most important application because they have huge effects on human life. The number of earthquakes from 18 June to 31 December is 1081 on the Relief web [58]. This paper reviews later studies that use previous machine learning techniques that make more accurate solutions (Table 4).

Table 4. Tools for building platforms and frameworks

Ref.	ML techniques	Data parameters
Tehseen. et. al [59]	federated learning (FL)	Seismic data, Climate data, Reservoir data
Li, Y.et al [42]	stacked autoencoder	seismic property, topography, geology, hydrology, and soil datasets.

Tahseen. et.al applied FL for seismic tremor expectation that empowered dispersed customers to cooperatively gain proficiency with a common forecast model without replacing the original place of training data. FL separates the ability to use machine learning from storing big data in the cloud. FL model achieved results better than ML models like k-nearest neighbor (k-NN), Multilayer perceptron (MLP), Decision Tree (DT), and Random Forest (RF) at the value of magnitude 5.0 [59].

Li, Y.et al applied a stacked autoencoder to look for robust highlights by spare advancement, and the classifier exploited undeniable level unique elements to recognize the earthquake-induced landslide spatially. The outcomes show that the proposed technique essentially outflanked traditional strategies, accomplishing an overall precision of 91.88%, while recorded logistic regression (LR), support vector machine (SVM), and Random Forest (RF) recorded 80.75%, 82.22%, and 84.16%, respectively [42].

5.4. Wind turbine fault prediction

Sensor innovation has been applied generally in different fields. An enormous number of sensors are likewise introduced on the wind turbine hardware to gather the operation data of the wind turbine. Given the gathered mass activity information, the wind turbine state data investigation strategy is utilized to anticipate the wind turbine fault. This technical analysis of the state data of the wind turbine from numerous layers uncovers the potential significant fault data of information by artificial intelligence algorithms, achieving the fault expectation of the fault turbine. Wind turbine fault prediction isn't sensitive to time sequences in the classical model. In [45] proposed CNN-LSTM model to predict the fault of the wind turbine. Input data is represented as semantic sensor data explained by SSN (Semantic Sensor Network) ontology to extract useful information. The model proved on the yaw database of number 4 and number 12 of the icing fault database of the wind turbine. The results showed that the CNN-LSTM model is better than RNN, LSTM, XGBoost, and SCADA models in efficiency, and accuracy.

6. Conclusion

Recently, AI algorithms become more used in most environmental applications to predict. Detecting a particular algorithm depends on the type and the amount of data. The ecological sciences have a large group of issues amiable to headway by insightful methods. Deep learning achieved progress in environmental sciences according to an increasing amount of data. Ontology has a role in enhancing the results it extracts useful information and uses them as input data for AI algorithms. The AI algorithms that were applied in the applications (2020-2021), in this paper it achieved better efficiency and accuracy more than others.

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