Assessment of Machine Learning algorithms for automated monitoring

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Abstract: Artificial Intelligence and Machine Learning have made exponential progress in the last decade with a significant technological impact both on individual users and organizations in multiple domains of activity. The capabilities of AI applications, which were built using dedicated algorithms, have increased continuously, which enabled them to perform sophisticated processing tasks. Language, computer vision, autonomous driving, robotics, and automated application monitoring, which have been core problems in AI ever since 1950, have reached a new technological peak nowadays. This study aims to overview and classify Machine Learning algorithms based on certain predefined criteria. This classification can be used for the development of complex ML automation applications where the repetitive tasks performed by users would be taken over by the AI applications.

Keywords: AI, Machine Learning, supervised learning, reinforcement learning, automation.

Evaluarea algoritmilor de învățare automată pentru monitorizarea automată

Rezumat: Inteligența Artificială și învățarea automată au înregistrat progrese exponențiale în ultimul deceniu, având un impact tehnologic semnificativ atât asupra utilizatorilor individuali, cât și asupra organizațiilor din multiple domenii de activitate. Capacitățile aplicațiilor AI, construite folosind algoritmi dedicați, au crescut continuu, permițând sarcini de procesare sofisticate. Limbajul, viziunea computerizată, conducerea autonomă a vehiculelor, robotica și monitorizarea automată a aplicațiilor, probleme de bază în AI încă din 1950, au atins un apogeu tehnologic în zilele noastre. Acest studiu își propune să ilustreze o imagine de ansamblu și o clasificare a algoritmilor de învățare automată pe baza unor criterii predefinite. Clasificarea elaborată poate fi utilizată pentru dezvoltarea aplicațiilor complexe de automatizare ML în care sarcinile repetitive efectuate de utilizatori sunt preluate de aplicațiile AI.

Cuvinte cheie: AI, Machine Learning, învățare supravegheată, învățare prin consolidare, automatizare.

1. Introduction

Artificial Intelligence (AI), which is human intelligence simulated by using computer systems, proposed for the first time in 1956 by Professor John McCarthy from Dartmouth College, continues to be the focus of researchers and scientists in various fields of activity. Their goal was to develop intelligent machines that interpret aspects of the real world similarly to humans, understand natural language and learn from examples.

In recent years, the volume of data has grown exponentially from 2 zettabytes in 2010 to 79 zettabytes in 2021 and is expected to reach 181 zettabytes in 2025 (Statista, 2021). In 2018, the number of devices that were connected to the Internet was 17 billion and it is expected to grow to 35 billion by 2025. (Boncea et al., 2019). This data comes from different sources in science (astronomy, bioinformatics, medicine, physics, meteorology, environment, etc.), business (customer databases, financial transactions, equipment monitoring, speech recognition, surveillance) and social media.

Currently, in the research domain there are multiple research initiatives to develop increasingly complex systems with multiple components that interact with each other, such as autonomous car navigation, intelligent robots, etc. The successful management of such systems

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requires an understanding of the processes that underlie their behavior. It is expected that in the coming decades the processing, analysis and interpretation of large volumes of data resulting from complex systems will remain a constant concern for scientists.

At the beginning of the 21st century, two events occurred that fundamentally transformed AI and contributed to its expansion into several fields of activity. The first significant event was the development of graphics processing units (GPUs) and their widespread use, leading to an increased parallel processing speed and efficiency. The second significant event was the emergence of the concept of Big Data.

The concept of Big Data involves challenges such as gathering, storing, filtering, analyzing, searching, sharing, transferring, viewing, querying, updating and privacy of data. If initially it was associated with 3 key concepts, which are volume, velocity and variety, in 2016 it was associated with five key concepts: volume, velocity variety, variability and value (Jain, 2016).

The two events mentioned above have led to a resurgence of interest in AI, especially in academic circles and in fields and industries that generate large volumes of data that can be used to improve processes and services and increase profits.

Artificial intelligence is part of the category of emerging technologies that help organizations solve complex problems, initiate and automate tasks, and ultimately provide efficient services to users.

The field of AI has made exponential progress in recent years, having a significant impact both on individual users, organizations and public administration in various areas of activity. In terms of applications and their ability to perform complex language and image processing tasks, which represent the core problems in AI since its emergence in the 1950s, AI has constantly evolved.

According to current estimates, the value of AI in the worldwide software market is expected to grow from $12.5 billion in 2020 to $107.5 billion by the year 2028 (Statista, 2022).

Given the fact that the current level of AI technology development has not fully reached the stage of replicating human intelligence, research and development teams have made progress in various applications which were developed for the individual and society. For example, AI techniques are increasingly being implemented in healthcare to the point where intelligent robots perform highly precise surgeries. At the same time, extensive research is being carried out on the human brain that contributes to advances in AI, and newly developed applications support medical research. Thus, brain research contributes to and, at the same time, benefits from AI developments.

Governments and large companies in various economic sectors recognize the importance of this technology for science, economics and eGovernment and have a crucial role in the regulation and implementation of AI on a large scale. Also, incorporating the specific concepts into the education domain helps prepare the next generation that will use and develop AI applications (Sandu et al., 2019).

Section 2 assesses Artificial Intelligence landscape in Europe including the key domains where it is currently used, legal and ethical aspects, the degree of usage in public administration and the plans for AI development for the next 5 years. Section 3 positions Machine Learning in an AI, Data Science and Big Data ecosystem and overviews ML methods: supervised learning, unsupervised learning, and reinforcement learning and the major differences between them. Section 4 proposes a grouping of ML algorithms into categories according to several predefined criteria. The classification is useful for choosing suitable algorithms for developing machine learning applications.

2. AI in the European ecosystem

At European level, resilient, secure and reliable infrastructures and technologies are indispensable for ensuring compliance with European norms and values. A strong single market, fair competition and functional rules-based trade are key assets for the EU's economic success and resilience.

In 2020, the European Commission published the report "White Paper on Artificial Intelligence: a European approach to excellence and trust" which assesses Artificial Intelligence in Europe, highlighting technological advances in various fields such as security, medicine, agriculture, social media, robotics, industry, finance, etc. It also overviews the potential risks. By using AI in decision making proceses, wrong decisions can be made. At the same time, if appropriate security measures are not implemented, the confidentiality of the beneficiaries may be affected. Based on the European AI strategy, presented by the European Commission in April 2018, this document analyzes Europe's strengths, weaknesses and opportunities within the global AI market (European Commission, 2020).

According to the above-mentioned report Europe has a strong academic sector and algorithmic foundations for Artificial Intelligence which is a significant advantage. It also has many startups and companies that are developing services in the areas such as finance, healthcare, engineering and agriculture. According to the latest statistics, a quarter of all industrial robots are produced in the European area. On the other hand, it faces a shortage in customer application development as well as a deficit of AI investors.

The European Commission promotes and supports an ethical use of AI which involves respecting the fundamental values and rights of citizens, such as dignity and the protection of privacy. It also recommends that AI technologies should be developed in accordance with EU rules, so as to protect the fundamental rights of users, in order to increase citizens' trust in this type of system. The ethical recommendations were developed by a group of high-level experts from almost all Member States.

The European Commission has increased AI research funding by 70% over the last 3 years compared to 2016-2019, which amounts to €1.5 billion (European Commission, 2020), and proposes the development of a "Digital Compass" for translating the EU's digital ambitions for 2020-2030 in well-defined objectives and for increasing the chances of reaching these objectives. The compass will include an improved monitoring system to track the EU's trajectory in terms of the pace of the digital transformation, gaps in European strategic digital capabilities, as well as the implementation of the "Principles for Digital Development". The Compass will also include the means to establish key milestones along four major points. The first two are focused on digital capabilities in the areas of digital infrastructures and education, and the other two are focused on the digital transformation of business and public services.

The four cardinal points for mapping the EU digital trajectory are:

- Population and professionals with high digital skills;
- Digital infrastructures that are sustainable, secure and efficient;
- Digital transformation of businesses;
- Digitization of public services.

Through the Digital Europe Programme 2020-2027 projects in five areas with high potential for digital transformation at European level will be supported:

- High-performance computing;
- Artificial Intelligence;
- Digital skills;
- Cybersecurity;
- Implementation of digital technologies in all areas of society.

Automation, data analysis and natural language processing (NLP) are among the most important applications of AI that simplify processes and increase operational efficiency, thereby impacting a multitude of business areas. As a result of automation, the repetitive tasks performed by users are taken over by AI applications. Data analysis enables the discovery of new patterns in data sets which are helpful for organizations.

From a technological point of view, artificial intelligence has managed to transform several fields such as healthcare, education, finance, media, eGovernment, real estate, transportation, business, social media and eCommerce.

Significant results were obtained in the last decade in AI application subdomains, such as speech recognition, natural language processing, image processing, decision making, computer vision and robotic systems. Kaplan and Haenlein define AI as "the ability of a system to interpret data correctly, learn from it, and use what it has learned to achieve specific goals and tasks." (Kaplan & Haenlein, 2018).

In recent years, a series of innovative applications have been developed in multiple fields (Dumitrache et al., 2022) such as engineering, robotics, finance, medicine (Petcu et al., 2022) and transport. Examples of such significant developments are presented below (Stanford University, 2021).

Governments and organizations are now aiming to develop new digital skills to face challenges related to data quality, accountability, reliable information, user privacy and data security (Banciu et al., 2019).

The willingness of governments to use AI in public services is illustrated in the "Governmnet AI Readiness 2021" ranking, which evaluates 160 countries and their level of readiness. This ranking is based on 42 indicators that can be included in 3 main categories: government, infrastructure and technology. The results show that:

- The USA is at the top of the ranking, followed by Singapore and United Kingdom;
- Almost 40% of the participants have developed or are in the process of developing national AI strategies;
- Eastern Asian countries represent 25% of the first 20 countries in this ranking;
- Romania ranks 56th, after countries such as Malta (32), Bulgaria (42), Cyprus (44), Colombia (45), Indonesia (47), Oman (49), Serbia (52), Turkey (53), or Bahrain (55) (Fuentes, 2021).

In the upcoming period, it is necessary to responsibly educate the public about artificial intelligence benefits and dangers, clarifying that different categories and subgroups of users face very different risks. Such public education services must provide accurate and balanced information. Some organizations are already running operations for developing participatory models of public engagement. Such efforts will be vital for fostering public interest and capacity for democratic engagement in global AI issues.

Worldwide interest in Artificial Intelligence systems has emerged starting with the transition to digital governance and was amplified by the pandemic measures implemented by the governments. At the European level, it was mainly the Nordic countries and some Western countries that have developed national AI strategies, while the Eastern countries are still in the analysis phase or completely lack such strategies.

Complete autonomy is an important objective of AI systems but it doesn't stand as the ultimate goal. AI should be embedded in a community-dedicated system with a clear definition of automated and human decision factors. The successes in this domain in recent years have led to a turning point, and a rigorous analysis of the disadvantages and risks of large-scale AI implementation is needed. "Deep fakes" or algorithms that propose recommendations in essential areas can lead to erroneous actions or even cause physical harm to people. Minimizing the negative impact and increasing the positive one on society involves continuous research and development (Stanford University, 2021).

3. Machine Learning for Task Automation

Machine learning is a subdomain of artificial intelligence (AI) that applies particular methods and algorithms to data sets, simulating human learning, and with each new processed dataset, the accuracy of the machine learning model is improved.

The ML algorithms are trained to make classifications and/or predictions, by finding key information in projects involving large data sets. The retrieved information is used by stakeholders for making decisions within business processes.

Before ML was used, AI was used for automating business-level simple tasks. As a result, AI algorithms were built and used only for a particular domain. The use of machine learning algorithms enabled the development of large-scale AI applications. Also, with machine learning enhancements, AI systems started to evolve with each iteration.

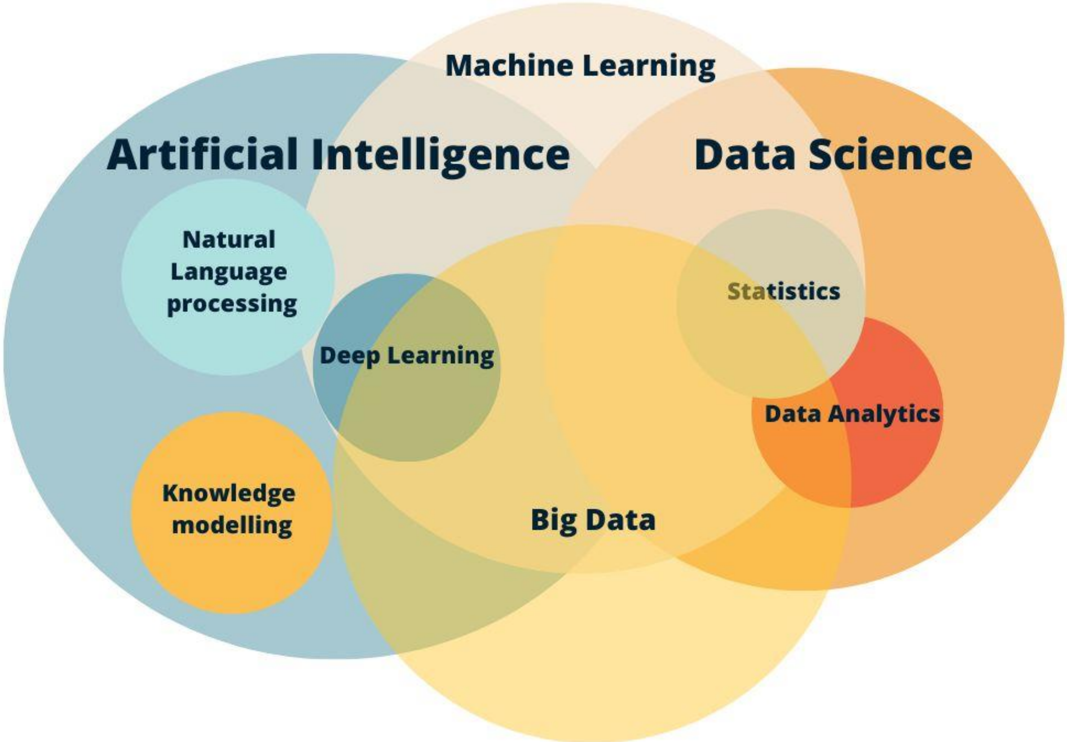

Figure 1. AI Machine Learning and Big Data (Source: own)

The major difference between Machine Learning and AI is the ability of the latter to continuously evolve. Through the use of several techniques, ML algorithms enable the processing of large amounts of data with the purpose of extracting useful information from it. Thus, after a consistent number of iterations, the results are extremely accurate.

Machine Learning is closely related to the concept of Big Data. The latter provides data that can be used by Machine Learning algorithms for learning. Given that this domain relies heavily on statistical methods, any type of artificial intelligence usually depends on the quality of its data set for consistent results (Figure 1).

If classical algorithms use rules and data that they process to get answers, Machine Learning uses answers and data to get rules.

A machine learning process involves creating mathematical and statistical algorithms that can accept input data and use a data analysis process to make a prediction:

1. The first step is to collect the data for the data set which shall be analyzed;
2. Once the data is collected, the type of algorithm to be used is selected, then a model is built;
3. The model is trained with the test dataset and used for making future decisions.

In Machine Learning a consistent and diverse data set is required to develop a robust ML solution. In today's online environment, companies collect a large amount of data about their customers. This data, which is large in both size and number of fields, is known as Big Data.

Big Data processing is time-consuming and difficult to perform by human standards. Such data sets are the best source for training machine learning algorithms. The more usable and machine-readable data there is in a large dataset, the more effective the training of the machine learning algorithm will be.

Machine learning algorithms have the ability to improve with training. Currently, most ML algorithms are trained using one of the three methods: supervised learning, unsupervised learning, and reinforcement learning (Figure 2).

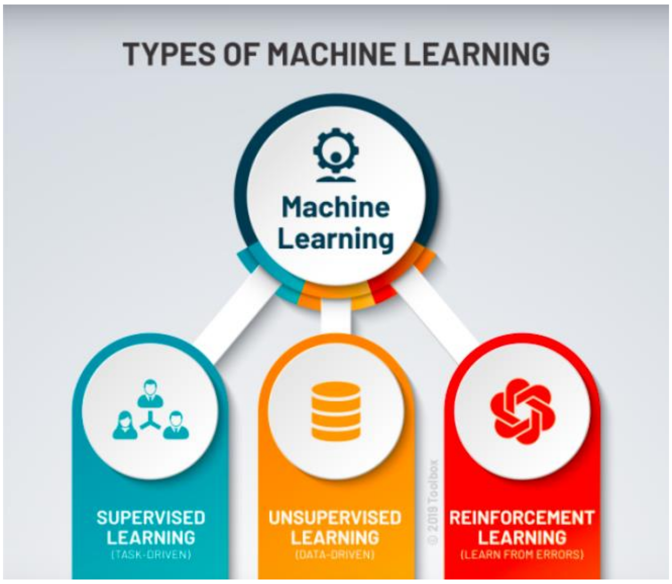

Figure 2. Machine Learning Classification (Potentia Analytics, 2019)

(Source: https://coschedule.s3.amazonaws.com/106308/910af4fa-63fa-4346-a2f2-ef280e8a250f/1576687016462.png)

3.1. Supervised Machine Learning

Supervised machine learning uses labeled sets of data to train algorithms so that they could classify or predict certain results with accuracy. In supervised learning, models are trained to make predictions based on a given data set. When new data input is injected into the model, it adjusts automatically. The algorithm searches for patterns in the given data in order to predict events based on new data sets. This labeled dataset includes attributes (properties) and observations (values). This type of learning is used when inputs and outputs can be clearly identified. Also, the learning algorithm can compare its predictions with the correct result and learn from this. Supervised learning can be used in multiple business scenarios, for example for detecting and filtering phishing and spam.

Examples of problems solved by supervised ML are classification and regression. Examples of methods used in supervised learning are linear regression, support vector machine (SVM) neural networks, naive Bayes, regression, random forest, and many others.

3.2. Unsupervised Machine Learning

Unsupervised machine learning uses algorithms to analyze and group by cluster data sets that are not labeled. The model is trained by adding new input data to extract general rules. The redundancy can be minimized through data grouping based on similar features.

This class of algorithms has the ability to reveal hidden patterns in data automatically, without the intervention of an analyst. The models search for the hidden information/structure by processing the unlabeled data. Unsupervised Machine Learning is mostly useful when input data is available and output data is not available. The model itself must identify the output data by grouping data that is not labeled by similarities or differences with no prior training. Due to its capability to label and group data, it is an ideal solution for data analysis, image and pattern recognition. Also, the dimensionality reduction functionality is useful for reducing the number of features in a model. Some examples of algorithms that are used in unsupervised learning include K-means clustering, Hierarchical clustering, Apriori algorithm, Principal Component Analysis, etc.

3.3. Semi-supervised learning

Semi-supervised learning combines unsupervised and supervised learning for predicting different outcomes. The data used as input is a mixture of labeled and unlabeled data. During the training process, semi-supervised learning uses a small labeled dataset to generate a classification and extract features from the larger dataset that is unlabeled.

Semi-supervised learning is useful in cases where there is not enough labeled data to train a supervised learning algorithm. For making an accurate prediction, the model must create structures and classify the data.

3.4. Reinforcement learning

Reinforcement learning is a machine learning model similar to supervised learning, except for the fact that the algorithm is not trained using data samples. The learning model for finding a solution to a problem is based on trial and error. A number of successful results will be consolidated to develop the best recommendation for a selected problem.

The IBM Watson system is an example of ML reinforcement learning. It is a computer system capable of asking and answering questions addressed in a natural language (Moroney, 2020), developed in the IBM's DeepQA project by a research team led by David Ferrucci (Ferrucci et al., 2013). The system used reinforcement learning to make decisions on the operations to be performed taking into consideration a particular context.

4. The Classification of Machine Learning Algorithms

There are many ML algorithms that can be used in different scenarios within an organization or project. ML algorithms can be grouped by several criteria and the most widespread is the way they work. The proposed grouping method helps to classify algorithms, but it offers great flexibility in positioning them in a certain category, as there are algorithms that can be placed in more than one category. To avoid duplicating them, the ML algorithms will be placed below in the appropriate section in a subjective manner.

4.1. Regression-based algorithms

Regression is a method used in statistics and within predictive models in machine learning. It enables the understanding of the relationship between independent variables (characteristics) and a dependent variable (outcome). Regression is extremely useful in estimating results in data analysis and is used for predicting results in predictive modeling.

Regression and classification are predictive modeling problems. Classification means defining categories of objects based on features that are learned, while regression enables the prediction of outcomes in a continuous manner.

Regression analysis is used for understanding the relationship between different characteristics and outcomes. ML Models are trained to make a forecast using regression techniques. The labeled training data enables the model to learn the relationship between input and output data. It can then make predictions concerning outcomes by analyzing new input data. Also, it can be used for understanding the gaps in registered historical data.

It must be noted, that special attention is needed when verifying that the labeled training data is representative of the total population. If it is not, the predictive model will be over-fitted to the redundant data. When the model is implemented this will result in predictions that are not accurate. A proper selection of features is required as regression analysis relies on the relationships between features and outcomes.

Today, regression models have many applications, especially in trend analysis, financial forecasting, marketing, time series prediction, etc.

The most popular regression algorithms are:

- Linear regression;
- Multivariate Adaptive Regression (MARS);
- Logistic regression;
- Stepwise regression;
- Locally Weighted Linear Regression (LOESS).

4.2. Instance-based Algorithms

The instance-based learning model involves a decision problem with relevant samples of training data that are important for defining the model. This method builds a database of sample data and compares new data with existing data using a similarity measure to make a prediction. The key aspects of instance-based algorithms are the representation of stored instances and the similarity measures used between different instances.

The most commonly used instance-based algorithms are:

- k-Nearest Neighbor (kNN);
- Learning Vector Quantization (LVQ);
- Support Vector Machines (SVM);
- Self-Organizing-Map (SOM);
- Locally Weighted Learning (LWL).

4.3. Decision Tree Algorithms

Methods based on decision trees build a decision model based on the actual values of the attributes in the data.

Decisions branch into tree structures until a prediction decision is made for a given record. Decision trees are a supervised method for learning and are used for classification and regression problems. They are preferred in Machine Learning due to their capability of returning quickly and accurately the results.

The most commonly used decision tree algorithms are:

- Classification and Regression Tree (CART);
- Iterative Dichotomiser 3 (ID3);
- C4.5;
- C5.0;
- CHAID (Chi-squared Automatic Interaction Detection);
- Conditional Inference Trees.

4.4. Bayesian Algorithms

Bayesian methods are those that explicitly apply Bayes' theorem to problems that require classification and regression. The most popular Bayesian algorithms are:

- Naive Bayes;
- Multinomial Naive Bayes;
- Gaussian Naive Bayes;
- Averaged One-Dependence Estimators (AODE);
- Bayesian Network (BN);
- Bayesian Belief Network (BBN).

4.5. Clustering Algorithms

Clustering algorithms are similar to Regression algorithms and comprise a class of problems and a class of methods. The main difference is that regression is a supervised learning algorithm while clustering is a type of unsupervised ML algorithm. Clustering methods are usually grouped by modeling approaches such as hierarchical and centroid-based. The methods are concerned with fructifying the data-inherent structures in order to organize this data into clusters considering the maximum commonality criteria.

The most popular clustering algorithms are:

- k-Mean;
- k-Medians;
- Expectation Maximization (EM);
- Hierarchical Clustering.

4.6. Learning algorithms based on association rules

Learning algorithms based on association rules extract rules that explain relationships between variables in the analyzed data. By applying this type of algorithms, companies can exploit commercially useful associations within large multidimensional sets of data.

The most popular learning algorithms based on association rules are:

- Apriori algorithm;
- Eclat algorithm.

4.7. Dimensionality reduction algorithms

Dimensionality reduction methods are similar to clustering methods. It analyzes and exploits the structure of the given data, but in an unsupervised manner. Another characteristic aspect is the fact that it describes the data using minimum information.

This feature can be useful for visualizing high-dimensional data or for simplifying data, as a preparatory step so it can then be used in supervised learning. Most of these methods can be configured to be used in classification and regression (Brownlee, 2019):

- PCA - Principal Component Analysis;
- PCR - Principal Component Regression;
- LDA - Linear Discriminant Analysis;
- PLSR - Partial Least Squares Regression;
- MDS - Multidimensional Scaling;
- MDA - Mixture Discriminant Analysis;
- QDA - Quadratic Discriminant Analysis;
- FDA - Flexible Discriminant Analysis.

5. Conclusions

The field of Artificial Intelligence has developed at an accelerated pace in recent years, having a significant impact on users and organizations in different fields of activity. The ability of applications to perform sophisticated language and image processing tasks has continuously evolved through sustained efforts of governments, academia, and businesses.

Machine learning frameworks are tools or libraries that allow developers to easily build ML models or machine learning applications without having to delve into the basics of algorithms.

The growing attention of governments towards different issues in the field of Artificial Intelligence and the various regulations that were developed reflect the understanding of the fact that the subject is complex and intersects with other priorities related to privacy, equity, and national and international security. The European Commission has included AI in the category of key areas to be supported in the next decade and promoted the use of AI systems in the fields of research and development, eGovernment, finance, agriculture, medicine and more.

In the paper a series of ML algorithms were analyzed and grouped according to similarities and their potential usage, having as a main criterion their modus operandi. This grouping method helps to, classify algorithms, but it offers great flexibility in classifying them as there are algorithms that can be placed in more than one category. To avoid their duplication in categories, they were positioned in the appropriate section in a subjective manner. The research is useful for scientists who aim to develop ML applications as it facilitates the choice of one or more appropriate algorithms for a particular use case.

At the same time, these series of specific Machine Learning algorithms were classified as a preparatory step for building automatic learning models and applications for use cases of automated monitoring. Future work will include the analysis and selection of dedicated tools for the development of adaptive systems for monitoring real-time Big Data applications.

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