Implementations of Machine Learning in Engineering, Bioengineering, Medicine and Psychology Fields

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Abstract. This paper presents definitions and implementations of 'Machine Learning' (ML) that have been discussed academically and applied in different fields such as Engineering, Bioengineering, Medicine, and Psychology. With the emergence of complex problems regarding data acquired by systems that are owned by institutions and organizations such as hospitals, manufactures, banks and other organisations, it is urgent that researchers and scientists should amalgamate their efforts and cooperate to find effective solutions to problems related to datasets. Solving such problems necessitates the introduction of enhanced machines and services for patients, customers, and clients. Thus, an effective solution lies in the invention of Machine Learning algorithms that can learn and solve problems related to huge datasets through various classifiers. Employing statistical computations, the results of such inventions reveal high accuracy rate and present the successful performance of ML algorithms.

Keywords: Machine Learning, algorithm, Engineering, Medicine, Bioengineering, Psychology, Support Vector Machine, K-Nearest Neighbour, Recurrent Neural Networks, and Convolutional Neural Network.

1. Introduction

In the 21st century, the era of technology, researchers and scientists have divided various sciences into sub-sciences to enable them to dig deeply for more details to find solutions for issues and problems faced in the preliminary science. In the realm of computing, new systems have emerged based on programming languages designed to achieve specific tasks with less time and effort. However, the need for innovative functions has prompted the scientist to control computer systems to be smarter and more intelligent in order to cope with human behaviour in many fields of life such as the medical, engineering, social sciences and other fields. Scientists have used Machine Learning (ML) to achieve such objectives. They construct algorithms to "think" and act like humans behave in certain circumstances to choose the perfect method based on the obtained dataset.

Most functions and processes in human life are now assisted by ML. For example, search engines learn how to get the most desirable results, anti-spam software learns how to refine email messages and the transactions based on cards used by clients of banks are protected by a software that learns how to investigate deceptions. Furthermore, digital cameras learn to

IMDC-IST 2023, October 25-27, Yola, Nigeria

DOI 10.4108/eai.25-10-2023.2348712

recognize faces and intelligent assistant applications on mobiles learn how to identify oral instructions. For car manufacturing, accident prevention systems are installed in cars through ML algorithms. Further fields are involved in ML algorithms such as bioinformatics, medicine and astronomy. Thus, scientists employ ML which is capable of learning and adapting [1].

ML is the fundamental technology to realise and improve artificial intelligence (AI) research, since AI is designed to study how to control the machine to be able to recognise and solve issues. ML is an important branch of AI that can satisfy the need for analysis and the prediction of human resource development (HRD) in the education field [2]. ML can be used for many purposes such as to obtain relevant data, to learn from data and to find solutions to problems that involve large datasets [3].

2. The Emergence of Machine Learning (ML)

Arthur Samuel was the first who coined the term 'Machine Learning' and defined it as a field of computer science that enabled computers to learn without being fully programmed [4]. ML is used for different computer tasks such as email filtering, detection of network intruders, optical character recognition, learning to organise and computer vision. In fact, computer vision, as an important branch of computer science, can process exclusively when joined to ML technology. ML can solve different problems in computer vision, this includes image recognition, item detection and tracking, automatic document analysis, face detection and recognition, computational photography, enlarged reality, 3D reconstruction and medical image processing [5].

Machine learning is an approach for improving practical software for computer vision, oral communication recognition, inherent language processing, robot control and other applications [6]. Accordingly, Mahesh[3] defined ML as "the scientific study of algorithms and statistical methods that computer systems use to perform a scientific task without being explicitly programmed". Thus, ML is used to give instructions to machines on how to deal with data more efficiently; therefore, if the algorithm cannot 'interpret' the obtained information from a dataset, ML is employed which draws on a large number of pre-existing datasets[3]. ML is described as a discipline that concentrates on two connected questions: How can one build up computer systems that automatically enhance via experience?; and what are the basic information-theoretic laws which computationally and statistically govern all learning systems, with the assistance of computers, humans and organisations? [6].

Carbonell et al. [7] discussed the concept of ML commenting that researchers have made great efforts to implant specific capabilities into computers. Therefore, the long-range solution in AI is to solve problems through ML in the modelling of learning processes. ML has been recognised within computer science, as a range of manufactures related to huge data issues such as consumer services, the management of logistic chains and the diagnosis of errors in complicated systems. ML has been involved in several fields ranging biology, cosmology to social science as shown in **Figure 1** that illustrates some current areas of ML implementation [6].

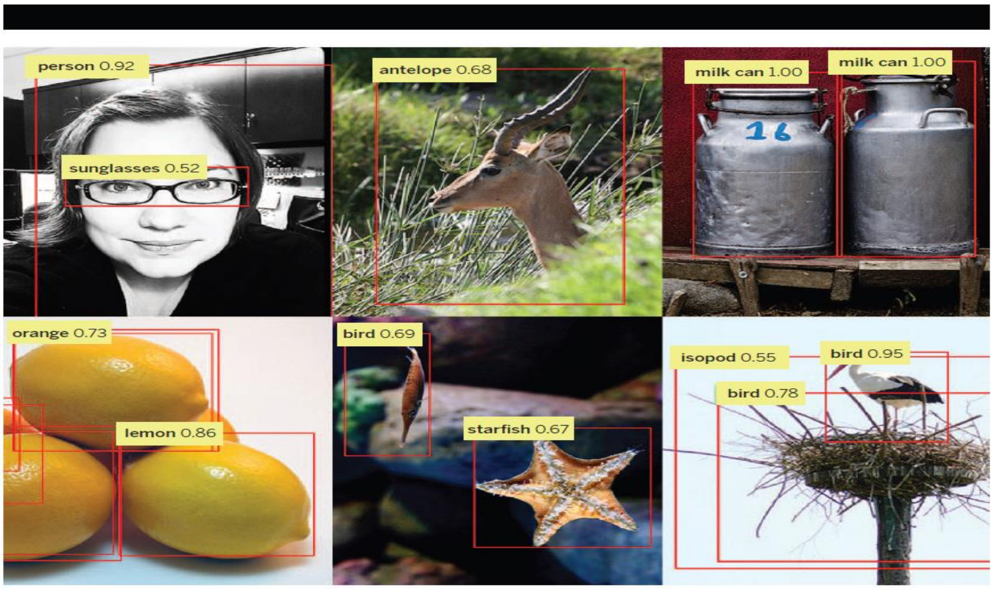

Figure 1: ML Implementations in Different Areas According to [6], The middle panel is adapted from [8], and The images in the bottom panel are from the ImageNet database; object recognition annotation is by R. Girshick

The three main fields that employ ML are: Computer Science; that essentially focuses on how to programme computers manually; Statistics; which concerns what valid conclusions can be deduced from data; and the human and animal learning in Psychology. ML is involved in choosing the proper computational architecture and algorithms that can be used effectively to acquire, save, organise, retrieve and merge various datasets. Furthermore, multiple learning subtasks are coordinated in a larger system for computational tractability. Other fields such as biology and economics can use ML to control theory for their environmental optimization and adoption purposes [9].

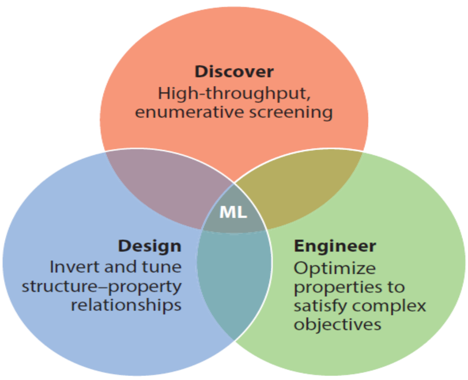

Figure 2: Venn Diagram of the Definition of ML in Computational Material Science According to [10].

According to Duan et al. [10], ML is defined by three key areas of opportunity in computational materials science: to discover, to design and to engineer new materials. This is illustrated in the Venn diagram shown in [10].

3. Implementations of Machine Learning (ML)

ML depends on concepts and techniques from many fields, such as the discipline of computational statistics, because ML requires the design of algorithms to execute statistical approaches on computers, as well as its application to other disciplines like AI, information theory, mathematical optimisation, biology, cognitive science and control theory [11].

According to Carbonell et al. [7], the field of ML is structured into three basic research foci, which are: (1) Task-Oriented Studies, which involves an engineering approach, this is related to the improvement and analysis of learning systems to enhance technical capabilities in a predetermined set of tasks, (2) Cognitive Simulation, that involves the investigation and computer imitation of human learning processes, and (3) Theoretical Analysis; which concerns the speculative exploration of the space of potential learning approaches and algorithms independent of application domain.

Methods of learning are divided into supervised learning, unsupervised learning[5], semi-supervised learning [3], integrated learning, deep learning and reinforcement learning [2].Supervised learning is categorised as classification (discrete) and regression (continuous), while unsupervised learning is categorised as clustering and dimensionality reduction that produce discrete and continuous data respectively[12]. Examples of supervised ML are: Decision Tree (DT), Naïve Bayes (NB), Support Vector Machine (SVM), K-nearest neighbour (K-NN) and Neural Networks including RNN and CNN. In contrast, examples of unsupervised ML are K-Means clustering, and Structural Topic Modeling (STM)[13].Examples of semi-structured ML algorithms are transductive SVM and self-training [3].

ML relies on huge datasets which are available in organizations that obtained the data from operations, products and customers. Additionally, engineers and scientists hold more complex datasets. For instance, medical care centres record all patients' information based on diagnoses and treatments; thus, it saves all outcomes of medical tests from measurements as distinct as Magnetic Resonance Imaging (MRI) scans and simple blood tests; bioinformatics saves a huge volume of data which can compare gene expressions in the DNA.ML is capable of achieving the optimal use of historical data to inform the construction of general models and to enhance the process of decision-making [11].

3.1 ML in Engineering:

In the USA, three significant reports have been authenticated for its strategic planning using ML. In May & October 2016, two reports have been released respectively by the National Security & Technology Council called "Preparing for Future of Artificial Intelligence" and "National Artificial Intelligence R&D Strategic Planning", which pointed out that the third wave of "explanatory and general artificial intelligence technology" would prematurely be ushered after the two waves of "focusing on human knowledge" in the 1980s and "the rise of machine learning" in 2015 [14].

For the engineering field, it is known that inverters are common sources of hardware outages that lead to energy losses at photovoltaic (PV) sites. An evaluation of a dataset to understand the failure rates within inverters is required to acquire insights from multiple characterization techniques. This includes diagnoses, analysis of data production and current-voltage curves.

Maintenance records that support the evaluation can log all site-related technician activities with different structures of information. Thus, in the USA, ML was employed to analyse 55,000 corrective maintenance (CM) records gathered from 800+ sites to recognize inverter-related records and effectively classify them among multiple CMMSs (Computerized Maintenance Management System) to obtain insight into relative failure rates within this crucial asset. Therefore, the number of continuing activities concentrated on reducing the levelised cost of energy (LCOE) of PV electricity; this deduces inverter reliability imitation analysis, replacement parts inventory management, cost model assessment for operations and maintenance (O&M) and the evolution of criteria for inverter testing [15-17]. Multiple records were gathered from multiple sites through the PV industry. Both supervised ML and unsupervised ML algorithms were operated for these records; SVM was used to recognise the records connected to inverters (supervised) and STM was used to gather inverter records into subcategories (unsupervised) as shown in **Figure 3** [13].

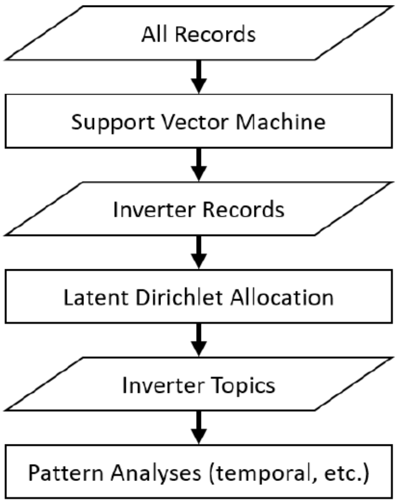

Figure 3: Dataset Processing and Analysis According to [13]

From 2008 to 2019, the sites inside the database reached commercial operation dates (COD). The sites outlined a total capacity of 4.9 gigawatts (GW) in DC, 3.8 GW in AC, with DC:AC relative rate falls of 1-1.5. Geographically, these sites covered 26 U.S. states with an important portion of sites (dependent on capacity) available in North Carolina, California, and Texas. Consequently, ML techniques enable the preparation of text-based data and collaboration to achieve reliable analysis, despite the deficiency of the standards in the operation and maintenance (O&M) data collection and management. The SVM algorithm achieved an accuracy of 90%, implying that the predicted inputs matched available labels 90% of the time. By contrast, STM does not achieve the required level of accuracy and achieved a probability of failure which reached 50%, and the results showed that multiple interpretable themes emerged from the CM records [13].

Similarly, the three cases of the classifiers K-nearest neighbour (KNN), Random Forest (RF) and Support Vector Machine (SVM) as ML algorithms were implemented on both imitated and measured radiation detection data to investigate the applicability of ML for detecting and predicting the position of a lost object from an existing radioactive sample. For each case, imitation attempts were executed through MCNP (Monte Carlo N-Particle) with different numbers of lost sources to imitate datasets for implementing ML algorithms. The results demonstrated that all algorithms performed accurately with results that were above 99.9%, and the location accuracy was above 97%. The SVM achieved a better performance that reached 0.5% and 0.2% higher location accuracy than the RF and KNN, respectively. Thus, ML algorithms can be trained on imitated detection data and implemented on data obtained experimentally. Furthermore, SVM, KNN and RF, as ML algorithms, could define the diversions effectively and provide the position of lost object from a radioactive sample [18].

3.2 ML in Bioengineering:

Certain health condition of patients is identified by Electroencephalography (EEG), which are signals to be taken on the surface of the scalp when connecting electrodes to the scalp with the use of conductive gel, to diagnose and treat different brain disorders such as epilepsy, tremor, concussions, strokes, and sleep disorders. ML is used in the bioengineering field as a method of analysis based on algorithms such as K-NN, regression tree RT and SVM to analyse EEG signals and in order to a particular problem. Each algorithm has a certain use case about the type of implementation and subject dataset [12].

Beheshti [19] conducted a study aimed at building a brain-age estimation framework and relied on a training set (788) of cognitively healthy (CH) individuals, using 22 different regression algorithms. Each regression-algorithm on separate test sets consisted of 88 CH individuals, 70 Mildly Cognitive Impairment (MCI) patients, as well as 30 Alzheimer’s Disease (AD) patients. Many regression algorithms have been used to predict the accuracy of the brain age, which are: SVM, K-NN, and regression binary decision tree ML algorithms. The results revealed that advanced ML algorithms can lead to effective high degree of accuracy in the prediction of the brain age. Specifically, the SVM algorithm achieved an average of 95% accuracy. However, the results of the regression binary decision tree showed poor performance. In conclusion, the SVM achieved the best overall training and testing results of all the other algorithms.

Similarly, Park et al. [5] presented a review to acquire the scope of different implementations of machine learning in the bioengineering field. Eight papers were reviewed to predict and diagnose various diseases such as Parkinson’s disease (PD), diabetic retinopathy, retinal blood vessels characterisations, gastrointestinal polyp detection, heart activity diagnosis, sleep staging through electrocardiogram and deep neural network and obstructive sleep apnoea. ML algorithms were used such as K-nearest neighbour (K-NN), naïve Bayes (NB), regression tree (RT), support vector machine (SVM) and convolutional neural network (CNN). ML algorithms performed to high degrees of accuracy at 97.93% in detecting and diagnosing decision in diabetic retinopathy. For the retinal blood vessels characterisations, the clustering method as an unsupervised ML algorithm was used and the accuracy achieved was 93.2% and 88.9% for both datasets (DRIVE and INSPIRE-AVR) respectively. SVM was used to detect gastrointestinal polyps and achieved an accuracy of 98.23%. The study demonstrated that the SVM algorithm resulted in a higher performance than for all other algorithms used in the accuracy context.

Fang et al.[20] proposed a wireless cardiovascular monitoring system that receive a non-stopped obtained data through a single-click to diagnose personalized healthcare. A scalable, water-proof textile triboelectric pulse sensor was utilised that relied on Machine Learning ML algorithms. The sensor functioned in a sweaty condition with the motions of an artificial body. For achieving high sensitivity with a single-to-noise ratio (SNR) of 23.3 dB, a response time (τ)

of 40 ms, and a sensitivity of up to 0.21 μA kPa^{-1}, structured carbon nanotubes (CNTs) triboelectric layer was used. The CNTs layer facilitated the textile triboelectric sensor along with the ML algorithms that controlled the blood pressure measurements. Furthermore, the textile triboelectric sensor was integrated with a processing circuit, a Bluetooth transmission structure, and a tailored mobile application to set up a wireless cardiovascular monitoring system as shown in **Figure 4**. The system could be connected to the internet for a single-click health data sharing and data-flow cardiovascular control. A neural network, as a supervised ML, was used to extract features of supportive information input values as HR, AI, RWTT, and K from gathered data. Subsequently, a well-trained algorithm with optimal model parameters was integrated for real-time blood pressure prediction. It was found that the integrated textile triboelectric enabled the wireless biomonitoring system to work effectively for cardiovascular system description.

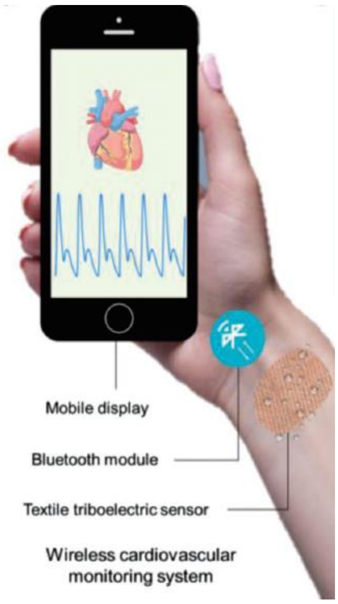

Figure 4: Design of a Textile Cardiovascular Monitoring System According to [20]

3.3 ML in Medicine:

ML is a very common technology that has been applied within the medical field. One of its most important applications has been for the diagnosis of one of the most common diseases which is breast cancer. SVM algorithms were enhanced using x-omics datasets that included vast amounts of data from various biological levels. The prediction accuracy relied on the quality of the data. The combination of different ML methods and a transcriptome dataset were used in the stratification of breast cancer subtypes (BCSs); however, the accuracy of methods differed based on the datasets or samples which were used. In contrast, the SVM with five-fold cross-validation classification using gene expression data, achieved 100% accuracy in prediction of intrinsic subtypes and 90% in prediction of the BRCA1 genetic variation, while predictions for BRCA2 and BRCAx genetic variations did not succeed.[21-23]. Overall, the prediction performance of SVM algorithms with radiomic data was importantly superior and almost without failure in differentiating BCSs [24].

In a Canadian study, medical imaging, such as X-ray and Computed Tomography (CT), were used as methods to diagnose Covid-19 disease. Computer-Aided Diagnosis (CAD) systems with the utilisation of X-ray and CT image processing techniques and ML algorithms assisted physicians to diagnose Covid-19 [25]. Another study [26] aimed at applying ML algorithms to diagnose Covid-19 disease using 15 deep convolutional neural networks (CNNs) as visual feature extractors, and 6 ML classifiers which consisted of: LightGBM, Bagging, Adaboost, Random Forest, XGBoost and Decision Tree. The CNN were: Xception, VGG19, VGG16, ResNet50, ResNet152, ResNet101V2, ResNet50V2, ResNet152V2, NASNetMobile, NASNetLarge, MobileNet, InceptionV3 InceptionResNetV2, DenseNet201 and DenseNet121.

The performance of the proposed method was approved on the existing Covid-19 dataset of X-ray and CT images. The best achievement was 99% classification accuracy by DenseNet21 feature extractor with Bagging tree classifier, followed by a hybrid of a RensNet50 feature extractor trained by LightGBM classifier with an accuracy of 98% as shown in **Table 1** below [26].

Table 1: Comparison of Precision Metric of Different ML classifiers The Bold Values indicate The Best Result and the Underlined Values indicate Second-Best Result of Respective Category According to [26]

	Decision Tree	Random Forest	XGBoost	AdaBoost	Bagging Classifier	LightGBM
MobileNet	89.00%	88.00%	93.00%	85.00%	99.00%	90.00%
DenseNet121	96.00%	97.00%	98.00%	95.00%	96.00%	95.00%
DenseNet201	94.00%	94.00%	95.00%	94.00%	98.00%	94.00%
Xception	92.00%	95.00%	90.00%	89.00%	98.00%	93.00%
InceptionV3	85.00%	85.00%	96.00%	85.00%	99.00%	82.00%
InceptionResNetV2	88.00%	96.00%	95.00%	90.00%	95.00%	93.00%
ResNet50	95.00%	89.00%	94.00%	96.00%	95.00%	94.00%
ResNet152	90.00%	91.00%	95.00%	91.00%	93.00%	89.00%
VGG16	94.00%	93.00%	94.00%	89.00%	92.00%	89.00%
VGG19	94.00%	93.00%	94.00%	89.00%	92.00%	89.00%
NASNetLarge	89.00%	91.00%	94.00%	90.00%	95.00%	91.00%
NASNetMobile	89.00%	87.00%	95.00%	88.00%	93.00%	88.00%
ResNet50V2	92.00%	89.00%	94.00%	88.00%	96.00%	91.00%
ResNet101V2	87.00%	89.00%	94.00%	86.00%	96.00%	78.00%
ResNet152V2	91.00%	94.00%	96.00%	91.00%	97.00%	91.00%

3.4 ML in Psychology:

ML may help psychologists improve their knowledge, abilities, and job professionalism. Human Resource Development (HRD) is an organization's planned activity to provide opportunity to obtain relevant skills and knowledge. HRD in smart education in the 21st century involves educating chosen persons to improve their learning and job skills as potential instructors, learners, directors, and supervisors via formal and informal learning.

China recognises the relevance of AI for infrastructure. China created the “Thirteen Five-Year Plan for National Science and Technology Innovation Plan” in August 2016. That idea was founded on the belief that AI will help China create contemporary technologies. The State Council of China announced the “New Generation Artificial Intelligence Development Plan” in July 2017. This strategy started the essential tasks for China to become the global leader in AI theory, technology, and application by 2030 [27]. Learner-HRD system interaction processes data from different instructional situations. Demographic, emotional, collaborative, and administrative data are collected. Virtual learning, LMS, MOOCs, social learning, cognitive tutor system, and online learning via computers and smartphones are examples [28].

A research also employed ML to improve people's capacity to meet community needs via HRD in smart education. To obtain HRD large data, integrated learning and deep learning methods like RNN and K-NN were employed for data mining. The objective was to enable learners create a learning plan and track their progress so instructors may modify teaching plans on time and pass appropriate suggestions for continual mass data. The research found that HRD lacked scalability and that ML techniques were not yet widely accepted [2] that supervised ML systems mimic human emotion recognition. Bota et al. [29] looked at emotion recognition utilising standard datasets, psychological signals, established elicitation materials, and assessment methods. ML algorithms, including NB, K-NN, SVM, LDA, and QDA, were utilised under supervision. SVM classifiers trained to recognise joy, sorrow, anger, and pleasure obtained 81.82%, 63.64%, 54.55%, and 30.00%, respectively. Accurate ML algorithms improved life quality and allowed the accumulation of vast data for trustworthy emotion identification systems.

Ji [30] created an interpretable model to predict suicide induced by anxiety, depression, and other mental illnesses. Deep neural networks (DNNs) were employed for automated detection. CNNs and RNNs have achieved impressive results. However, basic sets and classifiers failed to identify sophisticated suicide intents, hence suicide messaging explaining such activities are required to better understand suicide determinants. Since recent approaches used supervised learning techniques that needed human annotation, the study lacks data.

4. Results and Discussion

Many fields have used machine learning (ML) to develop tools, projects and conditions as in the field of psychology. The field of medicine was the pioneer for integrating ML into its practice and this has enhanced the devices and machines used to diagnose different diseases of patients or to predict the diseases before they develop or to limit the disease from becoming more malignant. As can be seen in **Table 2**, the field of medicine has achieved the highest rate of accuracy through ML implementation.

Table 2: Level of the Accuracy of ML in Different Fields

Field	ML Algorithm	Level of accuracy	Project/Tool/Condition
Engineering	SVM, STM	90%, 50%	Inverters in PV Sites
Engineering	SVM, RF, KNN	98%	Position of lost object from radiative sample
Bioengineering	SVM, KNN, DT	95%, DT: Poor	build a brain-age estimation framework (MCI, AD)
Bioengineering	KNN, NB, RT, CNN, Clustering SVM	97.93%, 93.2%, 88.9% 98.23%	PD, diabetic retinopathy, Retinal Blood Vessels Characterisations, Gastrointestinal Polyp
Bioengineering	Neural Network	effective	Wireless Cardiovascular System
Medicine	SVM	100%	Brest Cancer Disease
Medicine	CNN, RF, DT	99%, 98%	Covid-19 Detection

Psychology	Integrated Learning, RNN, Deep Learning, KNN	-	Human Resource Development (HRD)
Psychology	NB, SVM, KNN, LDA, QDA	81.82%, 63.64%, 54.55%, 30%	Emotion Recognition
Psychology	CNN, RNN	-	Suicide Prediction

Table 2 shows that the implementation of ML has led to the achievement of 100% accuracy in the field of medicine, especially for the diagnosis of breast cancer. Support vector machine (SVM) algorithms were enhanced by using vast amounts of data from various biological records, and the prediction accuracy achieved was 100%. Similarly, convolutional neural networks (CNN), random forest (RF) and decision tree (DT) algorithms were used for the prediction of Covid-19 disease and achieved a high accuracy rate of 99% and 98% for CNN and DT respectively.

Similar to bioengineering, ML algorithms were used to construct a brain-age estimate framework for MCI and AD patients. Supervised ML algorithms like SVM, KNN, and DT predicted brain age with 95% accuracy. DT algorithm predictions were bad. For brain diseases including Parkinson's Disease (PD), diabetic retinopathy, retinal blood vessel characterization, gastrointestinal polyp identification, and heart activity diagnostics, ML algorithms are accurate. Diabetic retinopathy diagnosis accuracy was 97.93%. For retinal blood vessel characterisations, the clustering technique obtained 93.2% and 88.9% accuracy for DRIVE and INSPIRE-AVR datasets. The SVM has the greatest gastrointestinal polyp detection accuracy of 98.23%. Wireless cardiovascular devices employ neural networks with acceptable accuracy.

ML algorithms have been utilised in engineering to estimate PV inverter failure rates with 90% SVM accuracy and 50% STM accuracy. To test ML's ability to detect and predict lost objects from a radioactive sample, three cases of the classifiers K-nearest neighbour (KNN), random forest (RF), and support vector machine (SVM) were applied to imitated and measured radiation detection data. The findings showed 98% accuracy.

Many Chinese psychologists have tried to use ML algorithms in HRD. Integrated learning, deep learning, RNN, and KNN algorithms have improved community service. The research failed, finding that ML algorithms in HRD had not been completely assessed and that HRD scale construction was still missing. Emotion recognition failed to predict suicide circumstances using CNN and RNN because basic sets and classifiers lacked adequate detection methods for complicated suicide intents. More datasets are required to understand suicide factors. However, emotion identification ML algorithms as NB, SVM, KNN, LDA, and QDA have obtained 81.82%, 63.64%, 54.55%, and 30% accuracy. These values varied but were lower than the medical SVM method. Thus, SVM is the most effective supervised ML algorithm, achieving 100% accuracy in one scenario and 99% and 98% accuracy in others, which are still ideal.

5. Conclusion

In this era, technology and the internet have been influencing our lives, whether directly or indirectly. In many fields such as medicine, engineering, and bioengineering, computer science has been integrated to facilitate diagnosing diseases, constructing new pathways, predicting and making the right decision, besides searching and solving problematic cases. Machine Learning (ML) as a branch of Artificial Intelligence (AI), and which is a significant division of computer science, has created a scientific revolution specifically in medical and engineering fields, and has achieved a significant level of performance.

According to the presented research studies, ML has become embedded in many fields as well as in projects that have been created and constructed for the welfare of people to have a healthy and luxurious lifestyle. This technology has created opportunities for industries, companies, and commercial organisations to present better lifestyles for patients, clients, customers, and users through integrating machines that can act and behave like humans. ML is one of the most developed algorithms that have been used in several fields. More specifically, SVM as a supervised algorithm has achieved the most successful results in learning and classifying datasets to be easier to use and then presented highly accurate results which enabled the diagnosis of problems and given the optimal solution within different fields.

Acknowledgment.
This work is partially supported by the UK Engineering and Physical Sciences Research Council (EPSRC) under grant EP/X039366/1, and HORIZON-MSCA-RISE ID: 101086492, Marie Skłodowska-Curie, Research and Innovation Staff Exchange (RISE), titled: FractuRe Orthopaedic Rehabilitation: Ubiquitous eHealth Solution (Robust).

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