The Development of the Artificial Intelligence in The Fields of Engineering, Medicine and Manufacturing Industries

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Abstract. This paper presents definitions and implementations of 'Artificial Intelligence' that have been discussed academically and applied in different fields such as Engineering, Medicine, and Manufacturing industries. Furthermore, the paper outlines the development of AI systems since its emergence to the present. With the emergence of black box of data acquired by systems that are processed during the system, it is necessary to transfer the black and the grey box into the white box to introduce enhanced machines and services for patients, customers, and clients. Explainable Artificial Intelligence XAI is able to transfer the black and the grey box into the white box. XAI can learn, explain *Why, When,* and *How* to solve problems involving huge datasets through various classifiers. This enables manufacturing industries to create new advanced products that meet the current market needs.

Keywords: Artificial Intelligence, Machine Learning, algorithm, Engineering, Medicine, Manufacturing Industries, eXplainable Artificial Intelligence, eXplainability, causability, Support Vector Machine, K-Nearest Neighbour, Random Forest.

1 Introduction

Science and technology have dominated the world in many fields not only to save the lives of people suffering from illnesses or poverty, but also to create a more comfortable and luxurious life for rich and wealthy people. Artificial Intelligence (AI) was integrated from the field of Computer Science and merged with other fields such as Engineering and Medicine to create new equipment and tools that continued to enable humans to utilise them for the welfare of people.

Evolving since the 1950s, it is now predicted that, within a few years, AI systems will be able to replicate human behaviour in all its forms including such features as cognitive, emotional, and social intelligence [1]. Firstly, it is important to present some definitions of AI drawing on the relevant literature. Colom et Al. [2] defined 'intelligence' in this context in terms of a "general mental ability" for reasoning, problem solving, and learning, while Allen Newell [3] asserted that 'intelligence' was the degree to which a system approximated a knowledge-level system. Many perspectives are related to the definitions of AI. For instance, AI is defined as "a system's ability to interpret external data correctly to learn from such data,

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and to use those learnings to achieve specific goals and tasks through flexible adaptation"[1], while Kok et al.[4] presented four definitions of AI shedding light on different angles of AI such that, as a field of computer science, AI was restricted to the evolution of computers that were able to connect in human-like reasoning processes. Such processes included learning, thinking, and self-correction. AI signifies the proposition that machines can be developed which possess the capability of simulating aspects of human intelligence such as learning, acquiring, and self-correction. Furthermore, AI can serve as an addition to human intelligence through utilizing digital tools such as computers. This has already been happening since it was used to create mechanical tools which then replaced human physical power. The fourth definition is that AI represents the study of techniques to use computers more effectively through enhancing programming approaches. Similarly, Stuart Russel and Peter Norvig set different definitions of AI that collapse into four classifications: acting like human, thinking like human, thinking with rationale, and acting based on rationale [5]. On the other hand, Grewal [6] has different a different perspective in defining AI as including the acquisition of knowledge relevant to a given subject. This knowledge included an 'understanding' the universe based on the five human biological senses through simulated mechanical sensors and non-biological sensors such as T.V, robot, camera, radar, computers, ...etc. Therefore, AI "is the mechanical simulation system of collecting knowledge and information and processing intelligence of universe: (collating and interpreting) and disseminating it to the eligible in the form of actionable intelligence".

Overall, all definitions fall in the same context and present similar ideas and functions of intelligence by means of tools and instruments, providing the required understanding and simulation for the desired human interactions.

2 The Emergence of AI

AI was first given attention in 1942 in the American short story "Runaround" by the famous author Isaac Asimov. This story was about a robot created by the engineers Gregory Powell and Mike Donavan who postulated the Three Laws of Robotics which were: (1) a robot may not harm or cause harm to a human; (2) a robot must execute orders and demands given to it by humans except orders that contradict with the First Law; (3) a robot must defend itself from attack as long as the defence does not contradict the First and Second Laws[1].

Concurrently, Alan Turing, the English mathematician, was developing a code breaking machine called "The Bombe" for the British government for the purpose of decoding the mystery Enigma code used by the German army in War World II. The Bombe which was very large and weighed a ton is considered to have been the first designed electro-mechanical computer. The Bombe had the capacity to break the Enigma code which was considered a mission impossible for even the greatest human mathematician. In 1950, Turing published his influential article "Computing Machinery and Intelligence"[7], in which he described how to develop and test intelligent machines. This Turing Test is still used today as a standard for identifying the intelligence of artificial systems such that: if a human is interacting with another human and a machine, and is unable to differentiate between the response of the machine and the human, then the machine is said to be intelligent[1].

In 1956, Marvin Minsky and John McCarthy who were computer scientists at Stanford University, hosted an eight week long workshop entitled the 'Dartmouth Summer Research Project on Artificial Intelligence' (DSRPAI) at Dartmouth College in New Hampshire. At this workshop, the term 'Artificial Intelligence' was officially coined. This workshop marks the initiation of AI and was funded by the Rockefeller Foundation. The main purpose of the

DSRPAI was to bring together researchers from different fields to create new research areas that aimed at constructing machines which were able to imitate human intelligence. Thus, it brought together those who would later be considered as the founding fathers of AI. Participants included the mathematician Claude Shannon, who is acknowledged as the founder of ‘information theory’. Also in attendance was the computer scientist, Nathaniel Rochester, who went on to design the IBM 701 - the first commercial scientific computer. A few years later, between 1964 and 1966, Joseph Weizenbaum created the famous ELIZA computer programme, which was a natural language processing tool capable of imitating a conversation with a human [1]. Subsequently, many attempts at Expert systems were invented such as IBM’s Deep Blue chess playing programme, in 1997, which defeated the world chess champion Gary Kasparov. However, these Expert systems could not be trained to identify faces or to recognise pictures of an apple or a tree. This is because, for such tasks, the systems must understand data correctly to learn from that data and then to use those ‘understandings’ to achieve particular aims and tasks through flexible adaption[8]. The flexible adapt is reflected in Artificial Neural Networks relying on the replication of the process of neurons in the human brain.

In 2015, Artificial Neural Networks appeared as AlphaGo, a program which was initiated by Google to defeat the world champion in the board game ‘Go’, which is more complicated than chess. AlphaGo reached the highest rate of performance using a particular type of Artificial Neural Network called ‘Deep Learning’ [9]. Recently, Artificial Neural Networks and Deep Learning have become the basis of most applications under the umbrella of AI. They represent the spine of image recognition algorithms used by Facebook, speech recognition algorithms that process smart speakers and self-driven cars.

3 The Concept of Artificial Intelligence AI

AI is a branch of computer science and, based on different definitions AI, it includes a broad range of perspectives. Accordingly, AI is often referred to as machine intelligence [10] to differentiate it from human intelligence [11]. Relying on the practical successes of machine learning (ML), AI has continued to attract significant interest since 1958 when McCarthy presented the Advice Taker as “a program with common sense” [12], which is considered a key dimension of AI. Therefore, current researches ensure that AI systems should be able to construct causal patterns of the world that advocate explanation and understanding rather than solving recognition problems [13].

According to the High-Level Expert Group [14], AI refers to systems that show smart behaviour through analysing their environment and taking actions with some autonomy to attain particular goals. Therefore, AI-based systems either can be basically Programmes that work in the virtual world such as voice assistants, image analysis software, search engines, speech and face recognition systems, or can be implants in hardware devices such as robots, autonomous cars, drones, and Internet of Things (IoT) applications [15].

Practically, ML is extracted from AI to enhance software that can learn from previous data automatically, in order to acquire knowledge from experience and to develop its learning behaviour slowly. The purpose is to build accurate predictability by continuously incorporating new data [16]. ML depends on large data sets and the development of new statistical learning algorithms with low-cost calculations [17]. On the other hand, Deep Learning (DL) as a family of ML is recently the most common method that is used to learn from data, because it relies on deep convolutional neural networks with long histories of information [18].

4 AI in Scientific Fields

Since intelligence depended on six key factors, which are: reasoning, understanding knowledge, capability to set plans, capability to learn, successful communication and amalgamation of competencies [19], different domains can be extracted from the general AI as shown in **Figure1**.

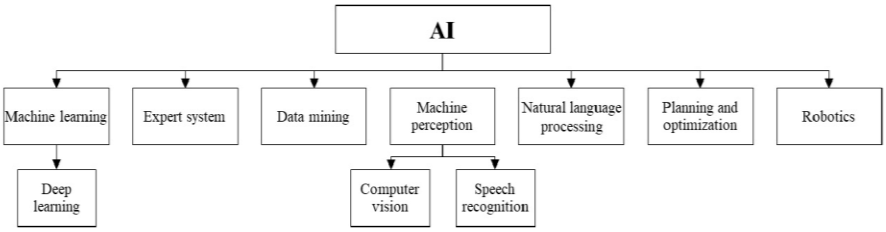

Fig.1. Different fields that are considered today as a subfield of AI/closely related to AI by [20]

According to Blake [20], AI has three main levels of evolution that are divided into stages: *Stage 1*- Artificial Narrow Intelligence (ANI), which is considered the lowest level of intelligence such that it works successfully for the task that it was designed for; however, ANI may fail for more complex tasks. The most common examples of ANI deployments are: speech & image recognition, Facebook's facial recognition, and Google map applications. Experts predict that *Stage 2* of AI will be achieved by 2040/2050 and will be known as Artificial General Intelligence (AGI). In *Stage 2*, the systems are much stronger than those of ANI because AGI will be able to argue rationally, organise, and solve critical problems in a wider context [21]. With respect to *Stage 3* - Artificial Super Intelligence (ASI), which is also known as High-Level Machine Intelligence (HLMI) - this is predicted to be achieved by 2080. ASI's are designed to reach higher levels of intelligence than human's cognitive capabilities in almost all domains and fields [22]. Therefore, Muller & Bostrom [23] believed that if *Stage 3* is achieved, then ASI's might be the last human-made inventions and that all future inventions would be accomplished by ASIs. Drawing on the latest AI literature, all fields have still only reached *Stage 1* of the AI levels. Different AI algorithms and systems have been used in many fields such as engineering, medicine, bioengineering, and other fields. In the following sections section, some AI implementations in the engineering and medical fields are presented.

4.1 AI in Engineering

Thon et al. [24] deployed AI in Engineering to find and construct approaches to reducing the number of experiments and simulations applied for the modelling to be as few as possible; more specifically, in process engineering and chemical engineering fields. Process Engineering is an area that is concerned with many subordinated fields such as mechanical, thermal, bio, electrochemical, and system-process engineering besides nanotechnology. In the field of process engineering, AI systems and algorithms are integrated in order to direct the change of raw materials into commercial solutions to be used in manufacturing industries, where these intermediary products and other products are combined to create discrete new products [25].

ML, and particularly DL, as branches of AI, were employed to solve such problems. DL empowers AI to reach its earlier expectations and to enhance developments in all fields of sciences resulting in the raising of the number of applications and increasing its usability [26]. The concepts of AI, ML, and DL are described clearly in **Figure 2.**

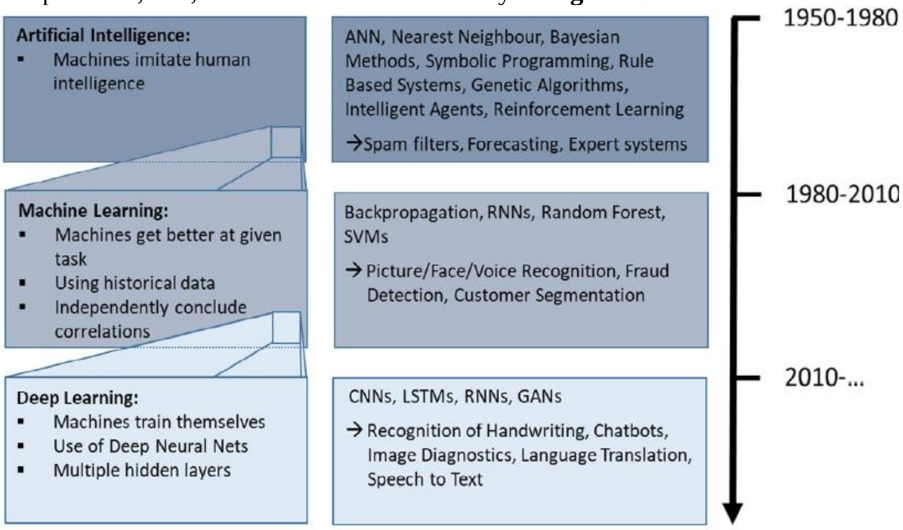

Fig. 2. Paradigms of Artificial Intelligence and related use-cases by [24]

When utilising AI methods in chemical processes, for example, several steps are required that necessitate breaking the process into aggregates or sub-modules. Then, the predictive AIs can then be trained, aligned and linked at a later stage. Therefore, appropriate data foundation must be explored before AI training to achieve a successful implementation of AI applications. Furthermore, pre-processing strategies and the final evaluation of the AI with different testing data, applications, and advantages of hybrid models are examined. The last step is to examine reverse engineering strategies for the purpose of splitting the trained practical black box or hybrid grey box models to mechanistic white box models. Thon [24] presented fields of activity in process engineering with significant tasks and achievements modified from Grossmann et al. [27] as shown in **Table 1**.

ML is a subtype of AI that enables the machine to reach conclusions or make predictions without being fully programmed for particular responses [39], where the machine is able to make changes and enhancements to algorithms without intervention from a programmer. On the other hand, DL is a subtype of ML that demands larger computing power and yields more reliable results. DL imitates the human brain and composed of several layers and operate as a set of connections between neurons such that the more layers available, the more complex is the machine's explanation [40]. Therefore, as many layers as the machine has, the human is stuck with difficulties in retracting and following the logic of the machine's conclusion, resulting in the "black box" problem: as a program becomes more independent, its algorithms become less comprehensible to users, including the original programmers [41]. As a result, these layers are considered "hidden" because of no reliable way to trace the machine's performance through these layers of reasoning as data is operated [33].

The term eXplainable Artificial Intelligence (XAI) denotes a set of techniques and approaches that can be used to transform the black-box AI algorithms to white-box algorithms, where the outcomes accomplished by these algorithms, variables, parameters, and steps taken by the algorithm to satisfy the acquired results, are explicit and explainable [28]. In

1987, Mercedes adopted the "Prometheus project" to invent the first robotic car to track lane markings and other vehicles [29]. Subsequently, ML and DL are being extensively used in autonomous cars for lane and object detection, perception, mapping, planning, route computation, and actuation [29-31], as well as the cloud fog computation which are the key components for many technologies and applications.

Table 1. Fields of activity in process engineering with important respective tasks and achievement; reproduced and modified from [27].

Process Design	**Process Operations**
Design of energy and energy recovery networks	Scheduling of process networks
Design of aggregates	Multiperiod planning and optimization
Design of aggregate networks	Data reconciliation
Hierarchical decomposition flow sheets Superstructure optimization	Real-time optimization
Design multiproduct batch plants	Flexibility measures
Process Control	**Supporting tools**
Model predictive control	Sequential modular simulation
Controllability measures	Equation based process simulation
Robust control	AI/Expert systems
Nonlinear Control	Large-scale nonlinear programming (NLP) Optimization of differential algebraic equations
Statistical Process Control	Mixed-integer nonlinear programming (MINLP) Global optimization
Process Monitoring	Sequential modular simulation
Thermodynamics-based control	Equation based process simulation

The significance of XAI technology is evident in its applications for vehicle inventions, relying on available autonomous car as a use-case and considering different integrals of autonomous driving from the explainability and transparency points of view, providing obvious interpretable and explainable solutions. The main purpose of integrating XAI into vehicle manufacture is to achieve high safety standards for drivers through presenting precise perceptions, planning, and activation including depiction of surrounding environment in the navigation decision making. The system should provide enough intelligence to predict possible future conversions besides being adaptable to current conversions [32].

The transparency and explanation of the AI-related solutions in vehicle manufacturing include some cases such that when the autonomous car makes unexpected decisions such as a wrong turn or direction, sudden brakes, inaccurate object recognition, or collision with other objects, then it is important to understand *why* it occurred in order to enhance the XAI model [28].

4.2 AI in Medicine

It is believed that AI systems have many deficiencies rather than benefits. For example, there is the AI systems' lack of peer-reviewed examined case-studies that are related to the roots of medical procedures and drugs. Besides, it may diminish the human interaction components of healthcare. Thus, AI currently lacks the development of personal relationships with patients. Furthermore, issues of human rights and security need to be considered when medical mistakes occur by the application of AI tools. There is no precise AI decision when or where liability will be allocated when AI system causes injury to a patient. Legal communities are required to overcome both internal resistance by experts and identify legal responsibilities to injured patients. Nevertheless, AI can contribute to the medical field through filling the gap between fallible human performance and perfection [33].

In 1960s, the field of radiology used programming to diagnose and detect the subtle signs of cancer or other abnormalities [34, 35]. Many years later, in 1998, The U.S. Food and Drug Administration [34] has approved the use of Computer-aided Detection (CADe) software for clinical purposes for the first time; then the Venters for Medicare & Medical services CMS also has approved its use in 2002. Digital mammography became possible in the early 2000s [36, 37]. Digital imaging allowed long-term enhancements in diagnostic care, through the collection of mammography results into training datasets to use in ML algorithms. Through digital images, radiologists can zoom and focus images during the estimation process, resulting in releasing the first version of computer programmes that enabled physicians to use image diagnosis. For instance, the CADe achieved 164% accuracy in detecting small invasive cancers which previously had reached an average of 5.3 years before detection [35]. Similarly, in 4,191 cases which were reviewed by radiologists who used CADe software as a double reader, the radiologists modified only 100 cases of their diagnosis [38], revealing that CADe is effective in detecting abnormalities but inaccurate in diagnosing the cancer [33].

According to relevant studies, AI systems have achieved accurate diagnosis equivalent to or better than physicians, and the elimination of human radiologists from diagnostic process presents an existential threat. Nevertheless, due to the fact that many medicolegal considerations are involved in AI system implementations for both diagnosis and treatment plans, there is, as yet, no successful integration of AI systems into complex healthcare. However, AI systems contribute minimising risks and ensuring the quality of healthcare.

The application of AI in the medical field has, so far, proved to be successful. The best example of such success is a current work of the Thrun group in which, using a DL approach doctors in the medical field found that such methods were able to categorise skin cancer more accurately in comparison to human dermatologists [42]. Another example is its successful application in identifying diabetic retinopathy and relevant eye diseases [43]. Within the medical field, the most desirable algorithm that AI might offer is *usable intelligence*, which is difficult to reach due to the problem of untangling the explanatory factors in the data to understand the conditions in an application domain besides learning from primary data, extracting knowledge, and generalisation tasks [44].

Holzinger [45] emphasised causability for medical applications rather than the eXplainability of AI systems, such that the causability is the property of a person whereas eXplainability is a property of a system. In medical decision support, datasets suffer from uncertainty, unknown, unfinished, imbalanced, diverse, wrong, lost and inaccurate data in random high-dimensional spaces [46, [47]. Therefore, challenges appeared in the integration, combining, and drawing plans for different distributed and random data to present visual analysis of these random data [48]. Thus, *explainable-AI* (XAI) must consider that different data may lead to a *relevant* result. Therefore, medical experts must have the possibility to *understand how and why* a particular medical decision has been made [49]. Consequently, XAI advocates confidence, safety, security, privacy, ethics, and trust [50], and presents usability [51] and *Human-AI interaction* into new significant contexts [52]. Thus, in the medical field, a system causability scale is urgently needed to evaluate the quality of an explanation [53], including social aspects of human communication [54].

5 AI in Manufacturing Industries

In this study, manufacturing means using AI systems with autonomous products to make desired things or offer engineering and medicine software. Machines, robots, and conveyors promote maintenance and material handling. Industries and manufacturers have a method to increase production, sell more goods, and make more money [55].

Manufacturing history is linked to machine tool dependability to reduce unplanned downtime [55]. Manufacturing system control influences factory decisions, physical duties, quality, and efficiency to build current items. The system's algorithms may determine what and how to create at the conclusion of the production process, when to utilise and gain resources, and when to release vacancy/operation sequence [56]. Industries aim to discover and isolate component antecedents or incipient defects, anticipate performance, and promote rational decision-making. Additionally, maintenance, prognosis, and health management are crucial. PHM systems revealed the health condition of machines and/or the production system in real time, diagnosed the source of deviations, and prevented failures to achieve near-zero downtime [57]. Machine manufacturing has moved from manual to automation using AI and ML [58].

The first use of AI in manufacturing is ML-based fault diagnosis [59], and the success of ML techniques depends on understanding a machine and its process, which produces physics-informed features from time, frequency, and time-frequency domain data [60]. SVM, KNN, and RF have been researched for induction motor defect diagnostics. Input signals included vibration, current, voltage, and flow. Statistical regression model parameters and temporal and frequency domain variables were retrieved [61]. Naïve Bayes, KNN, and SVM algorithms were used to diagnose induction motor faults using recent sensor information. Each approach is sensitive to various characteristics, although SVM performed best [62].

Similarly, selective laser melting SLM uses deep conventional neural network (DCNN) to assess surface textures and detect process errors. To prevent low-quality goods, process flaws may be properly diagnosed in time [63].

6 Results and Discussion

AI systems have dominated not only such scientific fields as Medicine and Engineering, but has also reached commercial industries where AI system have been used for wised production as well as to produce developed products and items such as tools and equipment that can be used by hospitals and profitable manufacturers. AI systems are currently splitting into more specific subfields, such as that which was started as general programming in Radiology to diagnose and detect the subtle signs of cancer and abnormalities as shown in **Table2**.

Table 2. AI Employment in Scientific Fields and Manufacturing Industries

Field/ Author	AI Algorithm/ system	Purpose of AI
Process Engineering	AI systems & algorithms	Change raw materials into commercial solutions
Engineering	AI systems & algorithms	Reduce number of experiments and simulations for modelling
Chemical Engineering	ML, DL	Change black box & grey box into white box

Process Engineering	XAI	Transfer black box into white box
Medicine- Radiology	Programming	Diagnose and detect the subtle signs of cancer/ abnormalities
Medicine	DL	Categorise skin cancer/ identify diabetic retinopathy & eye disease
Manufacturing Industries	AI systems	Improve productivity/ lessen unexpected downtime/ Decision making

Specific engineering sectors use AI systems to improve outcomes. The AI system's main purpose is to transfer the black box and grey box into white box, as used in process engineering and chemical engineering. Process engineering used eXplainable XAI to improve results, while chemical engineering used ML and DL. DL was also used to diagnose cancer and diabetic retinopathy. However, manufacturing industries have been using AI systems to improve productivity and reduce downtime, direct factory tasks, develop more efficient and high-quality products, detect part errors, and predict performance. The development of AI systems has been involved with different innovations as shown in **Table 3**.

Table 3. Inventions created using AI algorithms and Systems

Invention	Year of Invention	AI Algorithm/System	Purpose
ELIZA	between 1964-1966	Natural language programming	To imitate a conversation with a human
Autonomous cars: Mercedes	1987	ML, DL	Lane & object detection, mapping, cloud fog computations, …. etc.
IBM’s Deep Blue	1997	Expert system: chess playing program	To defeat the world champion Gary Kasparov
CADe	1998	ML	Detecting cancer
Digital mammography	2000s	ML	Zoom & focus images
AlphaGo	2015	Artificial Neural Networks: DL	To defeat the world champion in the board game Go
Vehicle	Recently	XAI	Safety for drivers/ predict possible conversions
Medical applications	Recently	XAI, Causability	Decision making/evaluate the quality of an explanation
Manufacturing industries	Recently	AI systems	Manufacture: machines/robots/ conveyors
PHM	Recently	AI systems	Disclosing the health state
Motors	Recently	ML: SVM, KNN, RF, Naïve Bayes	Fault diagnosis
SLM	Recently	DCNN	Analyse surface textures/ identify process fault detection

Between 1964 and 1966, ELIZA mimicked human communication as the first innovation. Mercedes production integrated the robotic technology in 1987, creating the first robotic automobile that tracked lane markers and other cars. Later, AI systems were developed to answer the questions “what, how, and when” for manufacturing, “how and why” for medicine, and “why” for engineering. Thus, contemporary inventions like cars and medical apps use the XAI algorithm to explain their decisions. Medical applications want 'Causability' reasoning for more exact XAI algorithm findings. Even if ML is the most frequent algorithm for all advancements, including autonomous automobiles, digital mammography, and motors, XAI is becoming the next branch of AI required in scientific and industrial domains.

ML and DL have been used to develop autonomous automobiles for customer-requested functionalities including lane and object identification, vision, mapping, route computation, actuation, and cloud fog computing. XAI is used in automobile manufacture to ensure driver safety and anticipate conversions, together with ML algorithms like SVM, KNN, RF, and Naïve Bayes for defect detection.

7 Conclusion

Implementations of AI systems have been extensively used in many fields and particularly, in engineering and medicine. Industries have been involved in acquiring AI systems to manufacture equipment and tools that enhance their services and achieve critical innovations in the fields of medicine and engineering. Consequently, industries study the needs of the market and tailor their systems to be aligned with their profits. For the present time, XAI is the most popular algorithm that is used in engineering, medicine, and manufacturing industries. As long as the need for more precise results of the XAI algorithm, new dimensions of AI continue to emerge for AI experts to create and innovate more efficient algorithms that satisfy their needs such as the ’Causability’”in the field of medicine.

This paper shows how the fields of engineering and medicine are competing in implementing the latest versions of AI systems to be applied in their innovations. In the future, most fields such as psychology, astronomy, embryology, and hospitality will be involved in integrating AI systems into their projects. The innovation of AI can present prediction, imitation, learning, and decision-making functions; however, it cannot represent human feelings, emotions, and intentionality.

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