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The Impact of Artificial Intelligence on the Medical Area: Detailed Review

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Abstract

Artificial Intelligence (AI), the most prominent technology of recent times, continues to make a name for itself with many studies not only in the field of software and informatics, but also in the health sector. AI, which has changed the direction of the healthcare industry, has tackled many issues such as data collection, machine learning, drug development, rare and genetic diseases. In this Review, we summarize the effects of AI on the healthcare industry under certain headings. We interpret the developments by discussing the effects, problems, and opportunities of AI from its first application in healthcare to the present day.

Keywords: Artificial Intelligence, Predictive medicine, Machine learning

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1. INTRODUCTION

Artificial intelligence (AI) is seen as the most promising technology in recent times to digitize healthcare services, strengthen the diagnosis and treatment of diseases, improve the experience of disease, and facilitate drug discovery. The use of AI technology in healthcare has a wide range of potential, from machine learning to drug discovery.

2. ARTIFICIAL INTELLIGENCE AND HUMAN HEALTH

AI has a very critical role in the diagnosis and treatment of diseases, especially in the health sector, and mainly describes the use of complex algorithms designed to perform certain tasks automatically [1,11]. Researchers interpret the data taking these algorithms into account and can even suggest treatment. AI contributes to many fields such as medical diagnosis, medical treatment, drug discovery, clinical research, pain management, and improving patient outcomes [1-3]. AI algorithms learn to produce the correct output for a given input in a new situation by analyzing data in all specified input-output pairs. The first approaches in AI had many successes in the 1970s [2,3] and have been shown to be helpful in many areas such as interpretation of ECGs, diagnosis of diseases [4], selection of appropriate treatments [5], etc. But building these systems in AI is costly. In addition, it is difficult to make different encoding. As a result, the future of healthcare and the future of ML and AI are interrelated. Due to the widespread use of AI in diseases in the health sector in recent years, and the spread of artificial intelligence, we decided to examine its positive effects in the medical sector in more detail [5-11].

2.1. *Ophthalmological Studies*

Studies revealed in the direction of deep learning, one of the sub-branches of artificial intelligence, laid the groundwork for ophthalmology. Due to the special anatomical structure of the eye, it has been useful for medical imaging, the advancement of medical diagnosis and the rapid development of image processing technology, and it has been shaped to revolutionize the diagnosis and treatment of ophthalmic diseases with AI technology. AI diagnostic technology uses color fundus photographs [12], optical tomography (OCT) image data, deep neural network learning, artificial intelligence in several eye diseases include glaucoma, cataracts, and age-related macular degeneration. Many AI products have been approved by the US FDA. These products support ophthalmology problems, inadequate resource allocation, and recurring problems with high accuracy and very fast support [13]. A new study by UT Southwestern shows that artificial intelligence can identify a specific genetic mutation in a glioma tumor with more than about 97 percent accuracy by examining 3D images of the brain. With this type of technology, common pretreatment surgeries, in which glioma samples are taken and analyzed to select the appropriate treatment for them, could potentially be eliminated [14].

2.2. Rare and Genetic Diseases

It has been proven that AI also gives very successful results on rare dis- eases. Focusing on deep learning, AI is being applied especially on rare diseases (RDs) for which insufficient data are obtained in basic and clinical studies. If looking at the studies on this subject, it is seen that only percent 5 of RD, whose number is more than 7000, has a cure. It is used in many areas from assembling the results, analyzing, and diagnosing. The use of artificial intelligence algorithms in diagnosis, drug discovery and preclinical research are among the benefits of AI [15]. Carter et al. described a new method, the variant effect scoring tool (VEST), which uses random forest (RF) to prioritize misperception variants that alter Protein activity. VEST has been applied to the exomes of the Miller and Freeman Sheldon syndromes, placing the causative genes among the top two only when Mendelian genes are considered. In the VEST method, which is a method with very high gains, allele frequencies are not necessary and continue to work even without controls [16].

RDs, although rare on a single individual basis, collectively affect approximately 350 million people worldwide. Currently, an average of 6,000 various rare diseases with a known molecular basis have been described, but it is not easy to make a specific diagnosis based on the clinical phenotype. Increasing integration of whole exome sequencing into the usual diagnosis of rare diseases is increasing diagnostic quantification. In addition, half of the patients do not receive a genetic diagnosis due to difficulties in variant detection and interpretation. In recent years, the use of RNA sequencing as a complementary diagnostic tool that obtains functional data has become increasingly common [15]. Looking at the data, it is seen that rare diseases (RD) with more than 7000 types affect approximately 350 million people worldwide.

However, it is a fact that only 5 percent of these people are treated. The development of new genome sequencing methods has accelerated the finding and diagnosis of rare diseases. In addition, many people who are sick go undiagnosed. Epigenetic has emerged as a promise for diagnosis and treatments in common disorders (e.g., cancer) with several epimarkers currently approved and used in clinical practice. Therefore, it may be an occasion to generate novel disturbance mechanisms and therapeutic targets in RDs [17]. In the era of "big data", the quantity of information produced, collected, and managed in biology has increased. The rapid and efficient collection, analysis and characterization of the said information is required [18]. AI has been successfully applied to decipher genomic information, especially in deep learning, core investigation, diagnosis, and drug discovery, and is accelerating in the epigenetic branch [19-21]. Application of deep learning to epigenomic studies in rare diseases can significantly improve symptom and treatment progress. This research aims to collect and briefly touch upon the applications of AI tools in the epigenomic field of RDs. Some studies on RDs show that this is a topic worthy of subheading, from the results obtained for the more common disorders [15].

Sorenson et al. used comparative genomic hybridization and RNA-seq to analyze chromosomal differentiation and dysregulated gene expression in tumor samples from patients with hepatocellular carcinoma. We used R for clustering of genes and other samples, while PAM method was used for clustering RNA-seq data. thus, they performed genomic and transcriptomic level analysis of RD by studying many gene sets [22].

Hierarchical clustering was used to examine the genome-wide methylome of uveal melanoma. It also showed that there is an indication of negative outcome of methylation of RAB31 (a member of the RAS oncogene family). Kilpinen et al. analyzed the whole genome and exome sequences except DNA methylation in retrospective and prospective cohorts of patients with medulloblastoma, thus providing specific evidence for genetic screening tests. Apart from that, K-mean, consensus clustering analysis of all CpG probes allowing identification of four consensus molecular subgroups, rare variant charge analysis determined genetic predisposition in at least two of these subgroups. Therefore, recommend using genetic testing, which is a standard care procedure for these patients [23].

There are uncertainties encountered in understanding the genetic data used to analyze the complexity of RD's, which does not have a treatment that may influence it, and the genetic mechanisms they contain. It motivates the use of AI methods and in-depth knowledge of molecular biology, which is crucial for finding suitable solutions in the design of drugs, including drug repositioning. It has been shown that the use of differentiated genetics, deep sampling methodologies is for finding significant data and greatly reduces the cost of research and development in drug design and has very positive effects on disease outcomes [15,24].

Looking at the results of" big data" analyzes related to medicine through AI, seeing that two important problems have been revealed: the insufficient number of samples compared to the amount of control variables that causes complexity. Apart from that, the results obtained have a natural noise level which proves the falsity of the predictions. The great heterogeneity that exists in the processes that contribute to disease and health creates the need to adapt medical care. Classical medicine, where decisions are made according to the disease and the common characteristics of the patient, instead of making an appropriate diagnosis when examined; precision medicine aims to shift medicine to prevention, customization and precision through genomics, AI, and biotechnology. It should be emphasized that the role of AI in the development of personalized medicine and treatments is important, as all this is crucial in shedding light on appropriate intervention targets and medical strategies to ensure the treatment of individual patients [15,24,25]. In the past years, it seems that practitioners rely on the opposite of artificial intelligence-based medical diagnosis. However, this AI should not be seen as a support provider to medical care. In later studies, it was aimed to use AI techniques to create more accurate diagnostic methods based on the regulation of data in the hospital to make the diagnosis of diseases such as cancer or cardiovascular diseases more successful. In addition, especially in recent years, AI is often used for many purposes in medical care, from medical diagnosis, preventive medicine, palliative medicine to drug design [15,24]. When investigating whether a computer aided diagnosis (CAD) program developed using deep learning convolutional neural network (CNN) on neck US images could predict the BRAFV600E mutation in thyroid cancer, it was decided that deep learning-based CAD for thyroid US could help predict the BRAFV600E mutation in thyroid cancer [26].

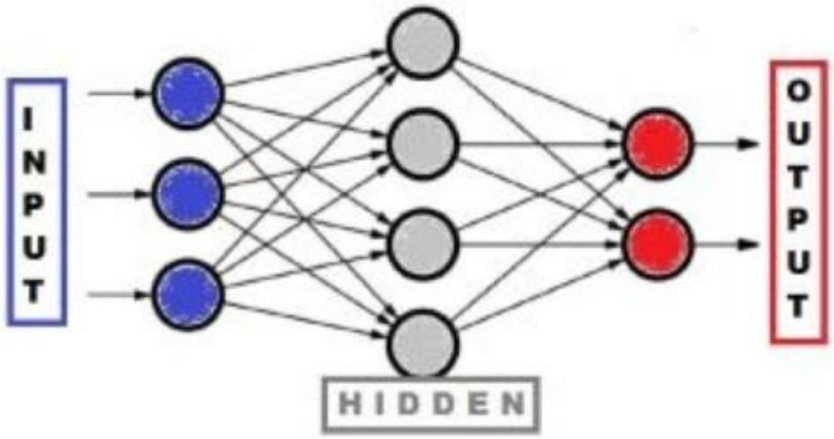

Figure 1. *Neural Network Structure. Source: Author*

The neural network, which is a computational model that operates similarly to the network structure between neurons, has certain processing elements. In addition to being composed of input-output layers, the model also has a layer that transforms the input information into a format that the output layer can use (Figure 1).

2.3. Diagnosis of Diseases

Diagnosis is very important for AI to use it to prevent diseases through methods that can identify the risks of developing diseases. Cardiovascular medicine represents a field in which AI is highly influential, as revealed by Li and his team, who analyzed the risk of heart attack using an artificial neuron network. Other studies have used machine learning to determine the risk of developing different diseases such as colorectal cancer, respiratory virus affinity, melanoma, death in smokers, depression or HIV transmission[26].

Looking at a different DL studies, it was emphasized that DL, especially convolutional CNN analysis, can diagnose chronic obstructive pulmonary dis- ease (COPD), detect severe respiratory disease (ARD) status and mortality in smokers. Using different statistical methods and using only computed tomography imaging data depending on the calibration types, the DL approach can detect smokers with obstructive pulmonary disease and determine which ones are more likely to suffer from respiratory disease and have the highest mortality rate. They found that from a population perspective, convolutional neural network analysis is a very powerful element for risk assessment [27]. With AI technology, situations such as collecting data on chronic diseases, tracking them and understanding diseases have been made easier. It was revealed by Sqalli and Al-Thani that AI and patient-employee relationship are effective in the process of developing commitment, providing information, providing motivation, reminder, prevention and creating a care network when they take into account inclusive issues on behalf of artificial intelligence-oriented medical coaching systems [28].

Type 1 diabetes, which often requires constant control through blood monitoring, physical exercise, diet, and insulin administration, has developed glucose monitoring (CGM) indicators for nearly 20 years. Today, when we look at the reviews on this subject, we see that a lot of effort is spent to pro- vide algorithms and various software applications to improve the treatment of Type 1 diabetes using the most up-to-date technologies as well as inter- operability. One of them is DSSs for advanced diabetes management [29-31]. With this application, the data of the people diagnosed with the dis- ease will be automatically analyzed and help will be provided to the person or doctor in the treatment adjustments. The data of these patients pro- vide resources for AI techniques to develop diabetes-related applications [32]. Considering the results, the importance of AI for patient-specific insulin bolus calculation and glucose estimation for patients with diabetes has been demonstrated. Diagnosing Parkinson's and tremor is seen as a clinical problem. In addition, correct diagnosis is seen as a vital issue to ensure the treatment and rehabilitation of people diagnosed with the disease. With the advancement of indicator technology and AI, very productive results have been obtained by using the most advanced technology to contribute to the diagnosis of the disease [32]. Dermatology is a field linked to morphological considerations. Many of the diagnoses made are based on the analysis of visual images. Dermatology is seen as extremely efficient in applying artificial intelligence image recognition capabilities for assisted diagnosis. Currently, skin imaging technology is manifested in dermoscopy, very high frequency (VHF) ultrasound, and reflectance confocal microscopy (RCM)[10,33,35].

In a 2017 study, discussed the relevance of skin tumor machines to DL. A CNN was trained using data from 129,450 clinical images containing 2032 different diseases. This is used to enable fine-grained objects to affect pixels and diseases. Then, a training model was created, which was used in the next model validation. In further model validation, results from ”keratinocyte carcinomas and benign seborrheic keratosis” and ”malignant melanomas and benign nevus” were compared with diagnostic data from 21 board-certified dermatologists. Thanks to CNN, there is an AI that can compare and accurately group skin tumors with dermatologists. Recent studies have compared the performance of neural networks trained with dermoscopy images to identify skin cancer with the grading of these images by dermatologists. This study used an advanced DL approach, with the goal of training a CNN with 12,378 open source dermoscopy images. In addition, 100 melanoma clinical images were used to compare the performance of CNN with 145 dermatologists. As a result, it was concluded that viewing dermatological images in a computerized environment would yield more accurate results compared to non-manual grouping of dermatological images [33,35].

Tschandl et al. noted how accurate state-of-the-art algorithms and manual diagnosis are in all medically relevant benign and malignant pigmented skin diseases. As a result, it has been understood that advanced CNNs are superior to humans in the diagnosis of pigmented skin lesions and have a more important role in clinical applications [34]. Processing and control systems dependent on AI have enabled the gradual improvement of mobile robotic exoskeletons used in upper extremity motor rehabilitation. Scans show the use of neural networks (percent 40), adaptive algorithms (percent 20), and other mixed AI techniques (percent 40). In addition, developments focusing on neuromotor rehabilitation were found in only percent 16 of the studies on the subject. In order to make the healing process positive and to improve the connection between doctors and patients, the technical qualities of the de- vices need to be improved [35]. Today, there are variables related to the care and health history of the patient. These variables may complicate patient diagnosis. In a published study, it was emphasized that 200 times more medical information will be produced than an individual can read in his lifetime. By automatically managing this data, AI can be seen as a major innovation in supporting clinical decision-making [36]. In a study conducted in a pediatric tertiary intensive care unit, it was aimed to distinguish and diagnose infectious sepsis from non-infectious forms of SIRS at an early stage, based on the distinction between the two diseases with very similar symptoms. Thus, a diagnostic type for ML, based specifically on a random forest approach, was developed, considering the 44 variables (basic characteristics, clinical/laboratory parameters, and technical/medical support) available at the time of patient admission. This type allows early diagnosis of all cases of sepsis, accounting for a percent 30 potential reduction in antibiotic intake in patients with non-infectious SIRS [37,38].

It is seen that many technologies have been developed and commercialized in patient-drug management. Proteus Digital Health has developed eating sensors and abdominal patches that allow patient-drug compliance through solution-oriented data-driven patient-drug management. Due to its advanced technology, it has a very important role in the pharmaceutical management market. But the downside was that it was overpriced and felt quite resistant when the customer used a sensor and wore a patch around their neck. AiCure used a smartphone to directly detect a patient medication adherence. In its clinical studies, it also uses technology to detect the status of AI-related drugs. According to AiCure, clinical research costs were reduced by increasing the current percent 58 to 62 percent clinical participant compliance to 92 percent. Also, it is dangerous to turn on the mobile phone every time for detection purposes, making the service difficult to always use. Smart Pill Bottle is an app that can manage medicines. The advantage of this ap- plication is the function of sounding the alarm in the smart medicine box during drug treatment, but the data on which drug the patients take and when is wrong. Due to the inaccuracy of drug data, a significant amount of purchases is not made in pharmaceutical companies and hospitals [40,41].

Looking at a study conducted in 2018, the image whose imaging performance was evaluated using PASCAL VOC and MS COCO recognition data was determined. Here, it is seen that perception is realized with the developed department. Enhanced pattern detection was managed using six consecutive activation maps. Six activation maps were then integrated to identify objects in each image through the model-trained model. It is applied in various fields, including object recognition, autonomous driving, CCTV, surveillance, and sporting events. In this study, fast R-CNN and faster R- CNN frames are used [42]. A study conducted in 2015 is also on this subject. In the study, each frame of human actions was divided into five parts by coding and the movements were defined. The movements determined the movement patterns according to the frames obtained by dividing the poses in the images into frames, and thus the movements were defined. In another study on this subject in 2017, feature values were extracted from each image using the CNN model. The poses were estimated by determining the weights of the joints in each image pose obtained. In addition, the weights extracted from the joints were sent to the pool layer and the resulting values were used to obtain the classes of the corresponding values via an LSTM model. Then, repetitive attention-attention network was used to realize human action recognition [43-45].

In 2019, Hong et al. conducted a recognition study of specific actions by tracking human actions related to objects around them. While analyzing, the Human Interaction with Common Objects dataset was preferred to recognize a specific activity based on people's interaction with the given objects, and RGB and stream flow values were extracted for the interaction images. Then, the pose and binary current values of the objects were extracted by using the RCNN mask to analyze the behaviors [39,46]. The relationship between the doctor and the patient is very important in terms of health service quality. Increasing patient satisfaction is important in terms of doctor-patient relationship. The relationship between people with chronic diseases and doctors is mostly established during physical examination in outpatient clinics.

The use of AI in relationships requires an intelligent system development in the hospital to increase patient satisfaction and establish a good doctor-patient relationship. Here, it is aimed to develop an intelligent physical examination system and to determine in advance the effect of this system on increasing the satisfaction of people with chronic diseases. An intelligent chronic disease management system related to AI has been established in relationships and thus combined with traditional Chinese medicine and western medicine. 115 people with chronic diseases who underwent a physical examination at the hospital from August to November 2019 were included in this study. 55 of them are in the smart system and 60 of them are in the traditional system. A questionnaire was applied to the patients who had a physical examination, and their satisfaction levels were determined and the scores between the two groups were compared [40]. A total of 106 patients were analyzed. It has been determined that there is no statistical difference between the smart system and those in the control system in terms of qualifications such as age, gender, education, or income level. As a result, it has been determined that the smart physical examination system is more effective in increasing the satisfaction of patients with chronic diseases. This is an important consideration in establishing a good doctor-patient relationship. Methods have been validated and presented in silico for smart dosing of type 1 diabetes prandial insulin. When identified among a population, the two algorithms have been shown to provide options for patients with Type 1 diabetes to improve insulin dosing, which includes multiple treatment alternatives [47]. Linear regression estimates dependent variables through defined independent variables. In the presence of categorized dependent variables (such as biomedical data), the logistic variable estimates the value and its associated probability [48]. Patients battling brain cancer for years to come may not need surgery to help doctors determine the best treatment for it. Many scientists have been experimenting with different imaging methods recently. But recent research identifies one of the most clinically applicable and accurate techniques to change this cancer assessment paradigm [49,50].

2.4. Cancer

Although cancer is the most common cause of death worldwide, it is thought that the number of cases will increase. Therefore, cancer research continues to be a top priority [51,52]. The integration of AI technology and cancer studies increases early detection, accuracy of diagnosis, and clinical decision-making, which is important in cancer. AI has a greater role, especially in regions with health disparities. The effects of AI in health and cancer are therefore very promising. Therefore, it is necessary to address the challenges that need to be overcome by increasing investments. AI has shown its effect in many types of cancer such as stomach, mouth, and ovary.

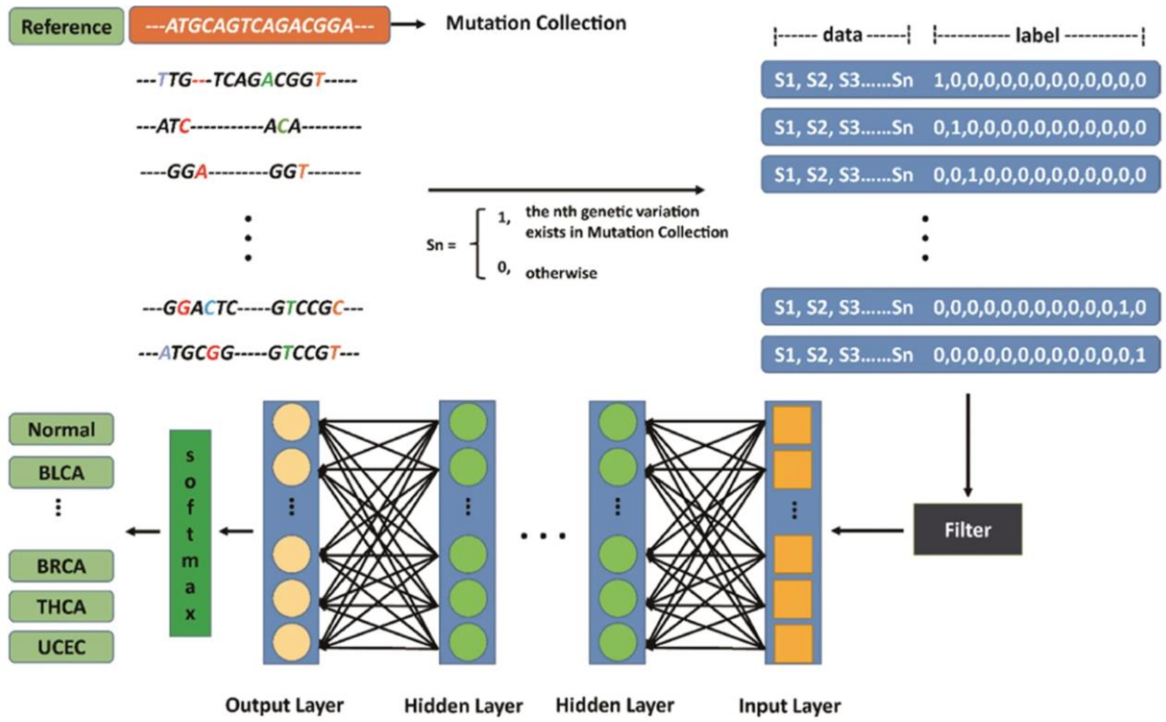

Figure 2: *Deep learning in cancer genomics [53].*

Genomic deep learning (GDL) consists of data processing and model training used for genomic studies. In the first step, after the point mutation file is obtained, the model entry is performed. After the model transformation is done, the data is filtered and the data processing part ends. In model training, there are regression layers [53].

AI technology is frequently used in gastric cancer, molecular bio-information analysis, endoscopic detection, chronic atrophic gastritis, early gastric cancer, depth of invasion, and pathology recognition. It is also used for the formation of certain preliminary models to evaluate lymph node metastasis in the stomach, response to drug treatments, and prognosis [54]. AI can also be trained and used for surgical guidance, such as surgical training, assessment of skills.

In oral cancer, as well as in gastric cancer, studies focusing on machine and DL methods designed to improve prognosis, patient survival in patients with oral squamous cell carcinoma (OSCC) and prediction models on recurrences in certain regions have been conducted. There are few studies investigating ML methods on OSCC digital histopathological images. It is thought that more research at the whole image level is needed and future collaborations with computer scientists can advance the field of oral oncology [55].

AI-related genome studies show great promise. With the cost of genome sequencing falling, the use of a supercomputer to analyze genomic data from cancer patients enables faster identification of genomic mutations [56]. However, for these identified mutations to be of outreach to the patient, it is necessary to clarify their relationship to clinical phenotypes[57]. To make these clinical comments, it is necessary to have a good command of the literature and science. There are many articles and new databases that summarize the relationship between genomic variation and disease [58,59]. The frequency of databases affects AI studies. With the increasing number of databases, the use of AI will also increase. Before AI is applied to genomic data, specific coding is performed to indicate the presence or absence of four bases (ATGC). Then the table is brought to a one-dimensional state. DL supports genomic studies by allowing multitasking learning, as it can learn multiple different tasks at the same time. It optimizes the differences in predicted and actual value using algorithms and minimizes these differences. It also allows multi-modal learning for different data types [60].

AI is also learning how to ML and computer-based decision support systems are the most important tools in medicine. It continues to revolutionize healthcare by improving diagnostic accuracy, increasing efficiency of outputs, improving clinical workflow, reducing human resource costs, and performing the complex tasks currently entrusted to specialists [54]. These features, also counted in prostate cancer, can be particularly helpful in the management of prostate cancer, with increasing applications in diagnostic imaging, surgical interventions, skills training and assessment, digital pathology and genomics. Health management must quickly adapt to the new world that evolves and changes with AI, and urologists, oncologists, radiologists and pathologists must under- stand this evolving science and accept the development of highly accurate AI-based decision support applications. Machine learning will require collaboration between data scientists, computer researchers, and engineers. In a study, they found that the highest accuracy rate in the ML algorithm of XGBoost, which was used to determine whether AI could play a role in the prediction of pathological diagnosis of ovarian cancer from preoperative ex- aminations, was 0.80. Different results were found between the evaluation of their significance, the correlation coefficient of the features, the regression coefficient and the significance of the random forest features [55]. However, they determined that AI will play a role in the prediction of diagnosis.

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Integration of multi-layered data is important be- cause cancer is a highly complex disease. The application of AI to the analysis of large amounts of ”omics” (exome, transcriptome, and epigenome) data, as well as data on the susceptibility of patients with acute myeloid leukemia to anticancer drugs, resulted in the identification of drug susceptibility genes. It also analyzed 323 patients to identify genomic changes with potential clinical implications that were not recognized by traditional panels [62]. Wang et al. showed that using a correlation-based feature selector combined with ma- chine learning algorithms such as decision trees, naive Bayesian and support vector machines, classification performance at least as good as published results can be achieved on microarray datasets of acute leukemia and diffuse large B-cell lymphoma [63]. Yu et al. in 2016 investigated the tumor proteomic profiles and clinical features of 130 ovarian serous carcinoma patients analyzed by the Clinical Proteomics Tumor Analysis Consortium (CPTAC), estimated platinum drug response using supervised ML methods, and evaluated our prediction models by permission [64]. In 2017, they established the Omics AnalySIs System for Precision Oncology (OASISPRO), a web-based system to extract quantitative omics information from The Cancer Genome Atlas (TCGA). This system effectively visualized patients’ clinical profiles, ran preferred machine learning algorithms on omics data, and evaluated prediction performance using extended test sets. They stated that this system will facilitate omics studies on precision cancer medicine and contribute to the creation of personalized cancer treatment plans by identifying the links between omic and clinical phenotypes [65].

2.5. Radiology

Diagnosis is the most important step in diagnosing and detecting diseases in radiology. In this step, multiple medical imaging methods are used - X-ray radiography, computed tomography, magnetic resonance imaging (MRI) and positron emission tomography. Radiologists use these image collections for detection and diagnosis [66,67]. Radiological applications are based on imaging. For this reason, it is a very suitable area for the use of DL methods. Computational approaches for radiology diagnoses were proposed and applied in the 1960s [68]. With the help of advanced ML methods, many diagnoses such as pulmonary tuberculosis detection, diagnosis of pulmonary tuberculosis [69] and common lung diseases by chest radiography and breast mass are made accurately using images [70-73]. Such studies use a technique known as transfer learning, in which images are fine-tuned using rooted deep neural networks and then neural network connections using thousands of biomedical images [74,75]. Therefore, there are millions of parameters. For the training of these parameters, AI is used to make it effective for medical imaging classifications. For example, prominence maps and gradient-weighted class activation maps visualize the importance of each image region according to their classification and are very useful for identifying localized image features. In the visualization phase, maximum images of the neuron can be obtained and at the same time, it can be visualized by producing synthetic input images by maximizing the filter output. These detailed approaches try to make neural network models more interpretable [70,76].

2.6. COVID-19

Little is known about the AI for its role as a defining technology in the clinical management of COVID-19 patients [77,78].A review of ML studies in intensive care units prior to COVID-19 noted similar issues, such as insufficient sample size and under-verification of estimates. In addition, no study has addressed the scope and quality of all current AI applications for COVID-19 in intensive care and emergency units. That's why these applications were much needed during the pandemic period. However, due to the limited time to develop applications, it is thought that there will be quality problems in AI applications. In addition, it is thought that many AI applications may be redesigned for use during the pandemic period, including diagnostics, prognostics, monitoring and resource optimization. Examining the quality of existing AI applications will provide important data to make the development of AI applications more efficient in intensive care and emergency units during and after COVID-19. It is aimed to systematically review and critically evaluate the available data on AI applications for COVID-19 in intensive care and emergency situations, considering methods, reporting standards, and clinical applicability [78-80].

2.7. Drug Discovery

The drug discovery and development process is a very complex and costly method. however, this long process and cost can be improved with computerized approaches. Molecule research and decision-making process with ML can be supported by many statistical methods. It is possible to verify the target among many samples, identify the markers involved in the pathogenesis of the disease, and analyze the molecules and targets in various signal transduction pathways.

Practices vary in context and methodology, with some approaches providing accurate predictions and insights [81]. The difficulties of implementing ML are mainly due to the lack of interpretability and reproducibility of the results generated by ML, which may limit its applications. In all areas, systematic and comprehensive high-dimensional data still need to be generated [82]. With continued efforts to tackle these issues and increased awareness of the factors needed to validate ML approaches, the application of ML can promote data-driven decision-making and has the potential to accelerate the process and reduce failure rates in drug discovery[83].Drug design is seen as a challenging and complex process. Therefore, it is necessary to consider the current disease and drug paradigm carefully. The current understanding of drug design is that a drug should be able to restore homeostasis. The drug re-establishes the balance and eliminates the causes that cause the disease. The reason for the negative results of many experiments on this subject is that the mechanisms of action are not clearly understood [81].

The process is divided into two as early development and development. The duration of each process (hexagon) is determined with the arrows (Figure 4). Bioinformatics and chemo-informatics use AI applications to identify diseases and rationalize the development of new compounds. The idea in the fields of bioinformatics and chemo-informatics is to develop large-scale models that can jointly account for the interaction of inflammation descriptors and the properties of absorption, distribution, metabolism, and toxicity (ADMET). These applications are modeled to determine the relationship established with diseases using perturbation models. It has been determined that these models have many effects when applied to infectious diseases, immunological disorders, neurological pathologies, and cancer. Moreover, the new approach to drug discovery is known as the ”de novo multiscale approach”. Apart from the ADMET profile, various investigations were made following this model to explain the link between drugs and patients [84-87]. In fact, global models are needed because a goal-centered approach is responsible for the decline rates and low productivity in pharmaceutical research and development. Moreover, network system biology is very important to understand the effect of genetic and epigenetic factors on drug activities, in which AI plays an active role. It has also been used in drug design and discovery, repositioning drugs with AI technology, researching drugs produced for an existing diseased condition, and repositioning them for other diseased conditions. Especially in recent years, the spread of AI-based algorithms shows that it will provide great convenience in drug discovery for the coming years [88].In the last few years, the field of AI has largely moved from theoretical studies to real-world applications. Much of this spectacular growth is associated with the widespread availability of new computer hard- ware, such as graphics processing units (GPUs), which accelerate parallel processing, particularly in computationally intensive computations. DL and ML algorithms have greatly helped pharmaceutical companies in the last 2 years [89].

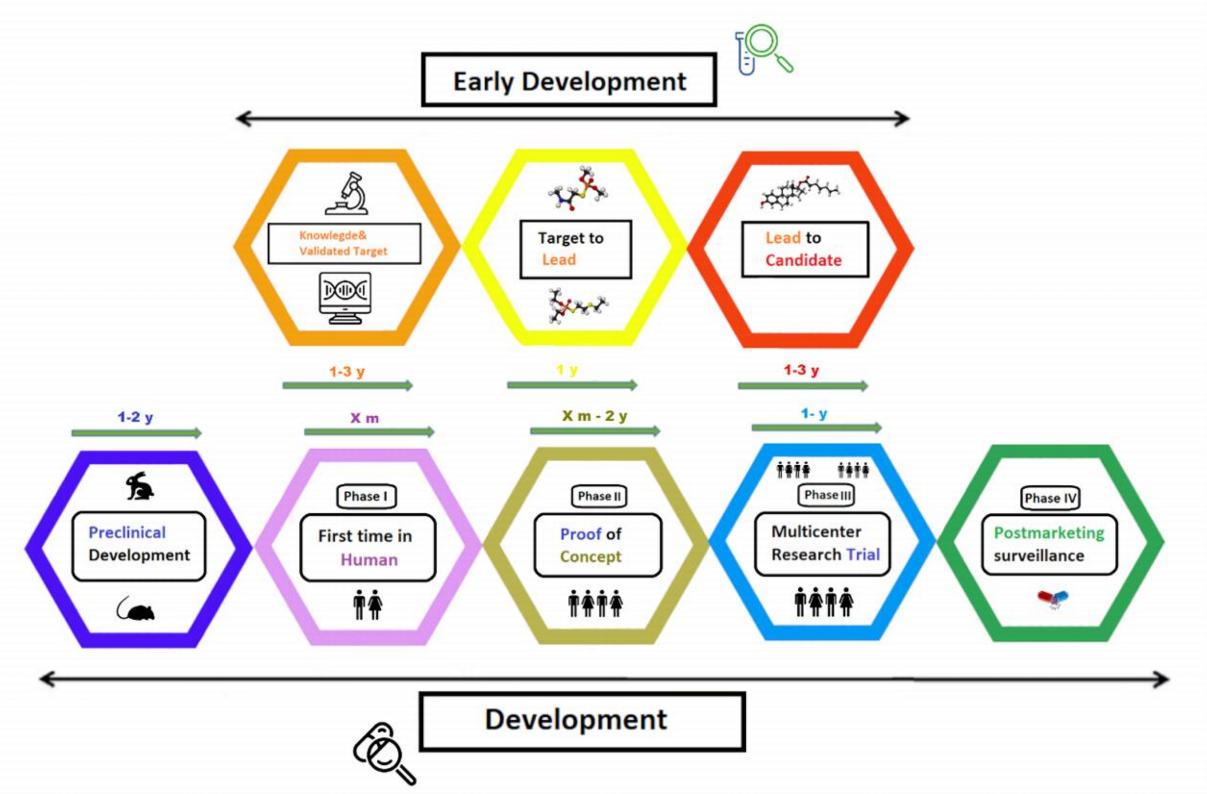

Figure 3. *Drug Discovery Process*

Figure 3. *Drug Discovery Process. Source: Author.*

3. CONCLUSION

In this review, we've outlined the tasks and roles that AI plays in various medical mission areas. We supported ophthalmology, genetic diagnosis and diagnosis, drug discovery, clinical diagnosis, and their impact on decision-making processes with research and publications. AI, which is effective in every field with its unique behaviors, will continue to support these areas. AI studies, which are positively correlated with the development of technology, rapidly increase its molecular and genomic performance. This increase is due to studies but is also affected by financial and health support. Of course, there are many technical and non-technical challenges currently limiting AI and its applications in healthcare. It is hoped that these challenges will be overcome and further integrated into health development and clinical areas. With interdisciplinary studies, different fields will integrate with each other and take a step towards groundbreaking studies.

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