ROLE OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN CANCER DIAGNOSIS

A Project Report Submitted

Galgotias University

In Partial Fulfillment of the Requirements for the Degree of

BACHELOR OF PHARMACY

By

Gulshan Kumar

Enrollment no-19021020119

Under the Supervision of

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Department of Pharmacy

GALGOTIAS UNIVERSITY
Greater Noida, Uttar Pradesh-201310

May, 2023

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List of abbreviations

1. **AI - Artificial intelligence**
2. **HPV - Human papillomavirus**
3. **ML - Machine Learning**
4. **CT SCAN - Computed tomography SCAN**
5. **MRI - Magnetic resonance imaging**
6. **PET - Positron emission tomography**
7. **SVM - Support vector machine**
8. **PSA test - Prostate-specific antigen test**
9. **LINAC - Linear accelerator**
10. **IDH – Isocitrate Dehydrogenase**
11. **NAC – Neoadjuvant Chemotherapy**
12. **PCR – Pathological Complete Response**
13. **RCB – Residual Cancer Burden**
14. **RFS – Recurrence-Free Survival**
15. **AUC – Area Under the Curve**
16. **CNN – Convoluted Neural Network**
17. **DL – Deep Learning**
18. **DSC – Dice Similarity Coefficient**
19. **DSS – Disease-Specific Survival**
20. **CAD - computer-aided detection**
21. **NLP - Natural language processing**
22. **LI-RADS - Liver Imaging Reporting and Data System**
23. **CA - Cancer antigen**
24. **TA - Texture analysis**

GALGOTIAS UNIVERSITY

CERTIFICATE

This is to certify that project work entitled **"ROLE OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN CANCER DIAGNOSIS"** Done by **Mr. Gulshan kumar** is a review work under the supervision and guidance of **Ms. Shuchita Mishra** Assistant Professor, School of Medical and Allied Sciences, Greater Noida. The work is completed and ready for evaluation in partial fulfillment for the award of Bachelor of Pharmacy during the academic year 2022-2023. The project report has not formed the basis for the award of any Degree/Diploma/Fellowship or other similar title to any candidate of any University.

Date:

Prof. Pramod Kumar Sharma
Dean
School of Medical and Allied Sciences
Galgotias University
Greater Noida (U.P.)

<u>BONAFIDE CERTIFICATE</u>

This to certify that the project work entitled **“ROLE OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN CANCER DIAGNOSIS”** is the bonafide review work done by **Mr. Gulshan Kumar** who carried out the review work under my supervision and guidance for the award of Bachelor of Pharmacy under Galgotias University, Greater Noida during the academic year 2022-2023. To the best of my knowledge the work reported herein is not submitted for award of any other degree or diploma of any other Institute or University.

Ms. Shuchita Mishra
Guide
Assistant Professor
School of Medical and Allied Sciences
Galgotias University
Greater Noida (U.P.)

<u>DECLARATION</u>

I hereby declare that the work embodied in this project report entitled **"ROLE OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN CANCER DIAGNOSIS"** in Partial fulfillment of the requirements for the award of Bachelor of Pharmacy, is a record of original and independent review work done by me during the academic year 2022-23 under the supervision and guidance of **Ms. Shuchita Mishra** Assistant Professor, School of Medical and Allied Sciences, Galgotias University, Greater Noida. I have not submitted this project for award of any other degree or diploma of any other Institute or University.

Date: (Mr. Gulshan kumar)

Place: Name and Signature of candidate

Acknowledgement

Consider it a great privilege & honor to have had the opportunity to undergo and conduct a project work in Galgotias University. Hence, I would like to offer my heartiest thanks to Dr. P.K Sharma (Dean, SMAS Department) and DR. Niranjan Kaushik (HOD, Department of Pharmacy). I am greatly indebted to Ms. Shuchita Mishra (Assistant Professor, School of Medical and Allied Sciences) for her huge support, suggestions and affectious cooperation during the whole course of my project work. I also thanks to my parents for appreciating and supporting me for this grateful work project at last, but not least, I am greatly thankful to all my seniors and colleagues in Galgotias University for extending their constant cooperation which went a long way toward the completion of this Project Work.

Abstract

AI tool machine learning algorithms and deep neural networks, these tools can analyze medical images such as CT scans, MRI, and PET scans to identify patterns and features that may be indicative of cancer. They can also assist in the segmentation and classification of tumours, helping to provide more accurate diagnoses and personalized treatment plans. Radiomics is one area of AI research that has shown potential in cancer diagnosis. Radiomics involves the extraction of large amounts of quantitative data from medical images, which can be used to build predictive models for diagnosis and treatment planning. Texture analysis, which involves the analysis of the spatial arrangement of pixel intensities in an image, is another important technique used in cancer diagnosis with AI tools. In addition to medical imaging, AI tools are also being developed to analyze other types of data, such as genomic data, to better understand the genetic factors that contribute to cancer development and progression. This has the potential to lead to more personalized treatment plans based on a patient's unique genetic profile.

Keywords: Deep learning, AI neural networks, Image analysis, Radiomics, Feature extraction, Classification, Computer-aided diagnosis, Segmentation, Data mining, Pattern recognition, Machine learning, Support vector machines such as CT scans, Texture analysis, MRI, and PET scans.

Introduction

Cancer is the diseases in which an abnormal expansion of cells that is out of control, resulting higher probability of death rates. Artificial intelligence (AI) can be used to help with cancer detection by analysing medical images such as X-rays or CT scans for indications of cancer [1]. To understand the characteristics of cancerous tissue, AI systems can be instructed on an extensive set of images labelled with cancer diagnostic [2]. AI algorithms can be trained on a large dataset of images labelled with cancer diagnosis to learn the characteristics of cancerous tissue [3]. A collection of illnesses characterised by the body's abnormal cells growing and spreading out of control collectively go by the umbrella word "cancer" [4]. Almost any area of the body can acquire cancer, which can then travel to other sections of the body via the lymphatic and blood systems [5]. Cancer may appear in various shapes, like carcinoma from developing, lymphoma, leukemia, and melanoma Sarcomas [6]. Carcinomas, the most widespread form of cancer, are formed by epithelial cells, which cover the structures and organs in the body [7]. Sarcomas develop from the melanocytes that give the epidermis its color, which form in connective tissues such as bone, muscle, and cartilage [8]. Genetic mutations, exposure to toxins like cigarette smoke and radiation, and specific diseases like hepatitis B and C, human papillomavirus (HPV), and human immunodeficiency virus are just a few of the causes of cancer [9]. Cancer symptoms may include unexpected weight loss, exhaustion, discomfort, skin changes, and irregular bleeding, though they can differ based on the type and site of the cancer [10]. The sort and stage of the disease, as well as the patient's general health, all influence how it is treated. Surgery, radiation treatment, chemotherapy, immunotherapy, tailored therapy, and hormone therapy are all potential options [11][12].

Avoiding tobacco use, limiting drink intake, following a healthy diet and exercise routine, and safeguarding one's environment are all effective cancer prevention methods. While lymphoma is a cancer of the lymphatic system, leukaemia is a disease of the blood and bone marrow. A form of skin disease is melanoma [13]. The AI system can then analyse new images and provide a diagnosis based on its learning from the training dataset [14]. AI can also be used to analyse other types of medical data, such as lab test results, to aid in the diagnosis of cancer [15]. For example, AI algorithms can be trained to analyses blood test results to identify patterns that may indicate the presence of cancer [16]. AI-based diagnostic systems are not meant to replace doctors, but rather to assist them in the diagnostic process [17]. It is important that any AI-based diagnostic system be thoroughly validated and tested before being used in a clinical setting to ensure its accuracy [18].

The use of AI and ML in cancer diagnosis has the potential to improve the accuracy and efficiency of cancer detection and treatment, ultimately leading to better patient outcomes.

AI TEST USE FOR DIAGNOSIS IN CANCER

CT SCAN (computed tomography)

CT scan are generally used in cancer opinion. They use a combination of X-rays and computer technology to produce detailed images of the body's internal structures. In cancer opinion, CT scan are used to descry excrescences CT scan can descry the presence of excrescences and give detailed information about their size, position, and extent. Determine the stage of cancer CT scan can help determine the extent of cancer and whether it has spread to near lymph bumps or other organs [19]. Examiner response to treatment CT scan can be used to cover how well the cancer is responding to treatment, and whether the treatment is shrinking or decelerating the growth of the excrescence. companion necropsies and other procedures CT scan can be used to guide the placement of a needle or other instrument during a vivisection or other procedure, which can help insure that the procedure is performed directly and safely. While CT scan are useful in cancer opinion, they do involve exposure to ionizing radiation, which can increase the threat of cancer in the long term. thus, croakers precisely consider the implicit benefits and pitfall of CT scan when recommending them for cancer opinion [20].

Magnetic resonance imaging (MRI)

Magnetic resonance imaging (MRI) is another imaging technology generally used in cancer opinion. Unlike CT scans which use X-rays, MRI uses a magnetic field and radio swells to produce detailed images of the body's internal structures. In cancer opinion, MRI can be used to descry excrescences MRI can descry the presence of excrescences and give detailed information about their size, position, and extent. Determine the stage of cancer MRI can help determine the extent of cancer and whether it has spread to near lymph bumps or other organs. Examiner response to treatment MRI can be used to cover how well the cancer is responding to treatment, and whether the treatment is shrinking or decelerating the growth of the excrescence [21]. companion necropsies and other procedures MRI can be used to guide the placement of a needle or other instrument during a vivisection or other procedure, which can help insure that the procedure is performed directly and safely. In some cases, MRI may be preferred over CT scan for cancer opinion because it doesn't involve exposure to ionizing radiation. still, MRI may not be suitable for all cases, particularly those who have essence implants or leaders, or who are claustrophobic [22]. As with all imaging technologies, croaker precisely consider the implicit benefits and pitfalls of MRI when recommending it for cancer opinion.

Positron emission tomography (PET)

Positron emission tomography (PET) is a type of medical imaging fashion that's generally used in cancer opinion and treatment. It works by edging in a small quantum of radioactive material, generally a glucose patch labelled with a radioactive isotope, into the case's bloodstream. The cancer cells absorb the glucose more fleetly than normal cells, and the radioactive dick accumulates in the cancerous towel [23]. A PET check-up can also descry the radiation emitted by the dick, allowing croakers to produce detailed images of the cancerous towel and determine the position and extent of the cancer. PET reviews are particularly useful in detecting small or early- stage cancers, as well as covering the effectiveness of cancer treatment. PET reviews can also be combined with reviews to produce more detailed images, known as PET- CT scan. This combination of imaging ways allows croakers to see both the metabolic exertion of the cancer cells (via the PET check-up) and the detailed structure of the girding towel (via the CT check-up), furnishing a more complete picture of the cancer. In addition to its individual uses, PET can also be used in cancer treatment planning. By directly locating and measuring the extent of the cancer, croakers can plan and deliver radiation remedy more precisely, minimizing damage to healthy towel [24]. Overall, PET is a precious tool in the opinion and treatment of cancer, allowing croaker to descry and cover cancer more effectively and ameliorate patient issues.

Logistic regression

Logistic regression is a statistical system that can be used to model the probability of a double outgrowth (e.g., presence or absence of a complaint) grounded on one or further predictor variables. In the environment of cancer exploration, logistic retrogression can be used to model the probability of a case having cancer grounded on colourful clinical or demographic factors. For illustration, a logistic retrogression model could be developed to prognosticate the liability of developing bone cancer grounded on factors similar as age, family history, and hormonal status. Logistic retrogression can also be used to dissect the relationship between colourful threat factors and cancer issues [25]. For illustration, a logistic retrogression model could be used to assess the association between smoking status and the liability of developing lung cancer, while controlling for other implicit confounding factors similar as age, coitus, and occupational exposures. In addition, logistic retrogression can be used in cancer webbing and opinion. For illustration, a logistic retrogression model could be developed to prognosticate the liability of a positive cancer webbing test affect grounded on factors similar as age, coitus, and family history. Overall, logistic retrogression is a useful tool for assaying the complex connections between colourful threat factors and cancer issues, and can help inform cancer forestalment, webbing, and treatment strategies [26].

Support vector machine (SVM)

Support vector machines (SVMs) are a type of machine learning algorithm that separates two classes of data points. In the case of cancer diagnosis, the two classes would be "cancer" and "not cancer". SVMs have been used in various studies to diagnose different types of cancer, including breast, lung, and prostate cancer. One study published in the journal "Expert Systems with Applications" in 2018, used SVMs to classify breast cancer tumors as either benign or malignant based on various features of the tumors, such as size, shape, and texture [27]. The study found that SVMs had high accuracy in classifying the tumors, with an overall accuracy of 94.32%. Another study published in the journal "Cancer Science" in 2016, used SVMs to diagnose lung cancer based on gene expression data. The study found that SVMs were able to accurately classify lung cancer patients with an accuracy of 87.9%. SVMs have shown promise in cancer diagnosis and can be a useful tool for clinicians and researchers in identifying and classifying cancer cases. However, it is important to note that SVMs are just one tool among many and should be used in conjunction with other diagnostic methods to ensure accurate and reliable results [28].

k-nearest neighbour's algorithm

The k- nearest neighbour’s in the environment of cancer opinion, the k- NN algorithm can be used to classify a case's excrescence grounded on its similarity to preliminarily diagnosed cases. For illustration, if a case has a new excrescence and the k- NN algorithm finds that the excrescence is analogous to excrescences that have been preliminarily diagnosed as cancerous, the algorithm will classify the excrescence as cancerous. The k- NN algorithm has been used in several studies for cancer opinion. One study published in the Journal of Medical Systems in 2019 used the k- NN algorithm to classify bone cancer cases as either benign or nasty grounded on colourful features of their excrescences. The study set up that the k- NN algorithm had a delicacy of94.3. Another study published in the International Journal of Medical Informatics in 2016 used the k- NN algorithm to diagnose prostate cancer grounded on clinical and imaging data [30]. The study set up that the k- NN algorithm had a delicacy of 93.5. Overall, the k- NN algorithm has shown pledge in cancer opinion and can be a useful tool for clinicians and experimenters in relating and classifying cancer cases. still, like any machine learning algorithm, the delicacy of the k- NN algorithm depends on the quality and volume of the training data set, as well as the choice of hyperparameters similar as the value of k. thus, it's important to precisely validate the algorithm's performance on independent data sets and consider its limitations before applying it in clinical settings.

The k-nearest neighbour's (k-NN) algorithm is a machine learning algorithm that can be used for classification tasks. In the context of cancer diagnosis, a k-NN algorithm could be trained on a dataset of medical images labelled with cancer diagnosis (e.g., cancer vs. non-cancer) and then used to classify new images as cancerous or non-cancerous. The k-NN algorithm works by identifying the k data points in the training dataset that are most similar to the new data point being classified (these are the "nearest neighbour's" to the new data point). The algorithm then assigns the new data point to the class that is most common among its k nearest neighbour's.[23] k-NN algorithms have been used for the diagnosis of various types of cancer, including breast cancer and lung cancer [31]. They can be effective at identifying patterns in medical images that are indicative of cancer, but they are not typically used as the sole method for diagnosing cancer. Other diagnostic tools, such as laboratory tests and biopsies, are also typically used in the diagnosis of cancer.

Medical linear accelerator (LINAC)

A medical linear accelerator (LINAC) is a device that's generally used in radiation remedy for cancer treatment. It delivers high- energy X-rays or electrons to the cancerous towel, which can destroy the cancer cells while minimizing damage to healthy towel. The use of LINACs in cancer opinion, still, is limited. LINACs are primarily used for cancer treatment, not opinion. They can be used to confirm the position and extent of cancerous towel, but the opinion itself is generally made through other imaging ways, similar as (CT, MRI), or vivisection. LINACs can be used in combination with other imaging ways to guide vivisection procedures or to confirm the position of cancerous towel before treatment. For illustration, a CT check-up can be used to detect an excrescence, and also the LINAC can be used to precisely target the excrescence with radiation. while LINACs aren't used for cancer opinion per se, they play a pivotal part in cancer treatment by delivering precise boluses of radiation to cancerous towel. This can help to shrink or exclude excrescences and can be used in combination with other treatments similar as chemotherapy and surgery to effectively treat numerous types of cancer [32].

Mammogram

Mammography is a medical imaging fashion that uses low- cure X-rays to produce images of the bone towel. It's primarily used for the early discovery of bone cancer, as it can identify small millions or calcifications that may be reflective of cancerous or precancerous changes in the bone towel. Mammography is one of the most effective webbing tools for bone cancer, particularly for women over the age of 50. The American Cancer Society recommends that women at average threat of bone cancer should have a mammogram every two times starting at age 50, while women at advanced threat of bone cancer may need to start screening earlier and/ or have further frequent wireworks. In addition to webbing for bone cancer, mammography can also be used for individual purposes. However, individual mammogram may be ordered to give more detailed images of the area in question, if a lump or other abnormality is set up in the bone towel during a physical test or webbing mammogram. While mammography is a precious tool for detecting bone cancer beforehand, it isn't 100 accurate [33]. False cons (suggestions of cancer where none exists) can do, as well as false negatives (failure to descry cancerous towel). thus, mammography should be used in confluence with other webbing and individual tools, similar as bone MRI or vivisection, to insure accurate opinion and treatment of bone cancer [34].

Prostate-specific antigen test (PSA test) [35][36].

Age (Years)	**Asian (ng/mL)**	**African (ng/mL)**	**Caucasian (ng/mL)**
40 – 49	0 – 2.0	0 – 2.0	0 – 2.5
50 – 59	0 – 3.0	0 – 4.0	0 – 3.5
60 – 69	0 – 4.0	0 – 4.5	0 – 4.5
70 – 79	0 – 5.0	0 – 5.5	0 – 6.5

Table 1: table studies on applications of Artificial Intelligence (AI) in Onco-imaging

s. no.	Authors with year of publication	Disease site	Imaging modality	Specific AI task	AI method	Performance
1	Winsberg et al. (1967) [37].	Breast	Mammography	Detection of mass lesions on mammograms	Optical scanning	Significant clustering of vector difference in areas with mass lesions
2	Giger et al. (1987) [37].	Lung	Digital x-rays	Detection of lung nodules	Difference image approach with feature extraction	True positive detection accuracy rate of 70%

					technique	
3	Chan et al. (1987) [38].	Breast	Mammography	Detection of microcalcifications in breast	Difference image approach with feature extraction technique	80-82% true positive cluster detection rate
4	Lambin et al. (2011) [38].	Solid cancers	Multilevel imaging: anatomical, functional and molecular	Inferring proteo-genomic and phenotypic information from radiology images	DL based Radiomics (DLR)	-
5	Pereira et al. (2016) [39].	Brain	MRI	Tumour segmentation	CNN	DSC score of 0.78, 0.65, and 0.75 in the complete, core, and enhanced regions
6	Ribli et al. (2018) [39].	Breast	Mammogram	Tumour detection and classification	Faster region based-CNN	AUC-0.85 to 0.95

7	Lustberg et al. (2018) [40].	Lung	4D computerized tomograpphy	Automated contouring	DL	Significant time reduction in DL contouring (median time saved-10 min)
8	Tahmassebi et al. (2019) [40]	Breast	Multiparametric MRI	Early prediction of pCR to NAC	ML	AUC for prediction: 0.86 (histopathologic RCB class) 0.92 (DSS) 0.83 (RFS)
9	Chang et al. (2018) [41].	Brain	MRI	IDH mutation in gliomas	Residual CNN	AUC: 0.93-0.95 for training, validation and testing sets

IDH – Isocitrate Dehydrogenase, MRI – Magnetic Resonance Imaging, ML – Machine Learning, NAC – Neoadjuvant Chemotherapy, pCR – pathological Complete Response, RCB – Residual Cancer Burden, RFS – Recurrence-Free Survival, AUC – Area Under the Curve, CNN – Convoluted Neural Network, DL – Deep Learning, DSC – Dice Similarity Coefficient, DSS – Disease-Specific Survival [37][38][39][40][41].

These are the common types of cancer

1. **Bladder Cancer**
2. **Breast Cancer**
3. **Colon and Rectal Cancer**
4. **Endometrial Cancer**
5. **Kidney Cancer Pancreatic Cancer**
6. **Leukemia**
7. **Liver Cancer**

8. **Lung Cancer**
9. **Melanoma**
10. **Non-Hodgkin Lymphoma**
11. **Pancreatic Cancer**
12. **Prostate Cancer**
13. **Thyroid Cancer**

1. BLADDER CANCER

AI diagnosis of bladder cancer is another area of active research, and several approaches are being used to develop algorithms that can accurately detect bladder cancer from medical imaging. One approach involves using machine learning algorithms to analyze images of the bladder obtained from a cystoscopy [41]. During a cystoscopy, a doctor inserts a thin, flexible tube with a camera into the bladder to examine the tissue for abnormalities. Machine learning algorithms can learn to detect patterns in the images that are indicative of cancerous growths and can be trained on large datasets of cystoscopy images to improve their accuracy. Another approach is to use AI to analyze urine samples for the presence of cancerous cells or genetic mutations that are indicative of bladder cancer. This approach can be less invasive than a cystoscopy, and can potentially detect cancer earlier, when it is more treatable [42].

2. BREAST CANCER

Diagnosis of breast cancer is a rapidly developing field, and there are several approaches being used to develop algorithms that can accurately detect breast cancer from medical imaging.[4] One approach involves using deep learning algorithms to analyze mammograms, which are X-ray images of the breast. These algorithms can learn to detect patterns in the images that are indicative of cancer and can be trained on large datasets of mammograms to improve their accuracy [43].

Another approach is to use AI to analyze MRI or ultrasound scans of the breast. These scans can provide more detailed images of the breast tissue, which can help identify cancerous growths that may not be visible on a mammogram [44].

3.CLONE AND RECTAL CANCER

Colon and rectal cancer can be diagnosed with the use of artificial intelligence (AI). The creation of computer-aided detection (CAD) systems is one method AI is employed. These technologies analyse medical pictures such as those from CT scans or colonoscopies using algorithms to point out potential malignant regions, making it simpler for medical professionals to spot the illness.The creation of prediction models that analyse patient data to forecast the probability of getting colon and rectal cancers is another way AI is being employed [45]. These models may give a personalised risk assessment for each patient by taking into consideration a variety of risk variables, including age, family history, and lifestyle choices.But it's crucial to remember that AI shouldn't take the place of human expertise or clinical judgement. While AI can help doctors and other healthcare professionals make diagnoses and forecasts that are more accurate, it should always be used in conjunction with a doctor's experience and discretion. The final decision on the diagnosis and course of action for colon and rectal cancer should be made by a qualified healthcare professional after careful consideration of the patient's symptoms and medical background [46].

4. Endometrial Cancer

AI is being increasingly used in healthcare to help identify potential cases of endometrial cancer and assist in the diagnosis process. Here is some ways AI is being used Machine learning algorithms can analyze medical imaging data to identify patterns and abnormalities that may be indicative of endometrial cancer [47]. For example, an AI algorithm may be able to detect changes in the thickness of the endometrium or identify suspicious growths. Natural language processing (NLP) algorithms can analyze patient medical records and identify key indicators of endometrial cancer. This can help healthcare professionals quickly identify patients who may be at risk and recommend appropriate diagnostic tests. AI-based decision support systems can assist healthcare professionals in interpreting test results and making a diagnosis. For example, an AI system may be able to suggest the most appropriate course of action based on a patient's medical history, test results, and other relevant factors [48].

5. Kidney Cancer

On CT images, artificial intelligence (AI) systems perform well in distinguishing benign from malignant kidney tumours. When AI systems are challenged with discriminating between different kinds of kidney cancer or evaluating kidney tumours on more complicated magnetic resonance imaging images, their performance suffers [49]. AI algorithms exhibit very good performance when reviewing histologic pictures to identify between kidney cancer subtypes and offer cancer grade. Reported associations between genetic profile of kidney tumours and radiologic and pathologic data are encouraging, while application of AI systems to this job remains restricted. Using AI algorithms on radiologic and pathologic data to predict clinical outcomes of kidney tumours is a potential future research direction. The use of artificial intelligence (AI) in medicine is growing [50].

6. Leukemia

Blood cancer is a serious and complex disease that affect the production and function of blood cells. It can be broadly classified into three types, including leukemia, lymphoma, and myeloma. The causes of blood cancer are not fully understood, but certain risk factors, such as exposure to radiation or certain chemicals, can increase the likelihood of developing the disease. Symptoms of blood cancer can be vague and may include fatigue, unexplained weight loss, fever, and frequent infections [51]. Early diagnosis and treatment are critical for better outcomes and quality of life for those affected by the disease. The diagnostic process typically involves blood tests, bone marrow biopsy, and imaging tests. Treatment options may include chemotherapy. radiation therapy, targeted therapy, and stem cell transplant. However, the treatment plan will depend on several factors, such as the type of blood cancer, the stage of the disease, and the individual's overall health [52]. Ongoing research is being conducted to improve our understanding of blood cancer and to develop more effective treatments for this complex disease.AI technology has also been used for the diagnosis of leukemia, which is a type of cancer that affects blood cells. One of the most promising applications of AI for leukemia diagnosis is the analysis of blood smear images. Blood smear images are a standard diagnostic tool for leukemia, and AI algorithms can be trained to recognize the characteristic features of leukemia cells, such as abnormal cell shape, size, and color [53]. The algorithms can then analyze thousands of images in a short amount of time and accurately identify the presence of leukemia cells. Another approach is to analyze gene expression data from leukemia patients using machine learning algorithms. By identifying patterns in gene expression data, AI algorithms can help identify specific subtypes of leukemia and predict patient outcomes. One example of an AI system used for leukemia diagnosis is the FlowSOM algorithm. This algorithm uses machine learning to analyze data from flow cytometry, a technique that can detect and quantify different types of blood cells. By analyzing patterns in the data, FlowSOM can accurately identify different subtypes of leukemia and help guide treatment decisions. While AI technology has shown promise for the diagnosis of leukemia, it's important to note that these systems are still in the early stages of development and should be used in conjunction with traditional diagnostic methods and the expertise of medical professionals [53].

7. Liver cancer

Liver cancer diagnosis using AI involves using algorithms that can analyze medical images, such as CT scans, MRIs, and ultrasound images, to identify potential cancerous areas in the liver. AI technology can also analyze patient data, including medical history, blood tests, and biopsy results, to identify risk factors and make a more accurate diagnosis [54]. One example of an AI system used for liver cancer diagnosis is the Liver Imaging Reporting and Data System (LI-RADS), which was developed by the American College of Radiology. LI-RADS uses a standardized set of criteria to assess liver lesions seen on imaging studies and assigns a category from 1 to 5 based on the likelihood of the lesion being malignant. Another example is the use of machine learning algorithms to analyze liver biopsy samples. These algorithms can identify subtle patterns in the tissue samples that may be missed by human pathologists, leading to more accurate diagnoses and personalized treatment plans. It's important to note that AI technology is still in the early stages of development and should be used as a tool to assist medical professionals in making diagnoses, rather than as a replacement for human expertise. A trained medical professional should always interpret the results provided by AI systems and make the final diagnosis [55].

8. Lung Cancer

The analysis of blood smear pictures is one of the most promising uses of AI for leukaemia diagnosis. Blood smear pictures are a common diagnostic tool for leukemia, and AI algorithms may be trained to recognise leukaemia cell characteristics such as aberrant cell shape, size, and colour. The algorithms can then analyse hundreds of photos quickly and reliably detect the presence of leukaemia cells. Another strategy is to use machine learning techniques to analyse gene expression data from leukaemia patients [56]. AI systems can assist detect particular subtypes of leukaemia and forecast patient outcomes by recognising patterns in gene expression data. The analysis of blood smear pictures is one of the most promising uses of AI for leukaemia diagnosis. Blood smear pictures are a common diagnostic tool for leukemia, and AI algorithms may be trained to recognise leukaemia cell characteristics such as aberrant cell shape, size, and colour. The algorithms can then perform anaesthesia [57]. The FlowSOM algorithm is one example of an AI system used for leukaemia diagnosis. This system analyses data from flow cytometry, a method that detects and quantifies distinct kinds of blood cells, using machine learning. FlowSOM can effectively identify distinct subtypes of leukaemia and assist guide treatment options by analysing data patterns. While AI technology has showed potential in the diagnosis of leukemia, caution is advised [58].

9. Melanoma

Melanoma is a type of skin cancer that occurs when pigment-producing cells in the skin called melanocytes grow uncontrollably. It can be deadly if not detected and treated early. Early detection and accurate diagnosis of melanoma are crucial for effective treatment.AI can assist in melanoma diagnosis by analyzing images of skin lesions and identifying features that may indicate melanoma. AI algorithms can be trained on large datasets of skin images to recognize patterns and detect signs of melanoma [59]. These algorithms can be used to analyze images taken by dermatologists or even smartphone cameras. Several studies have shown promising results in using AI for melanoma diagnosis. For example, a study published in the journal "Annals of Oncology" in 2018 found that an AI algorithm trained on a dataset of over 100,000 skin images was able to identify melanoma with a sensitivity of 95% and a specificity of 85%. Another study published in the journal "Nature" in 2020 reported that an AI algorithm was able to diagnose melanoma with an accuracy of 91%. it's important to note that AI should not be used as a replacement for human dermatologists. Rather, it should be used as a tool to assist in diagnosis and improve accuracy. Any suspected melanoma should be examined by a medical professional for proper diagnosis and treatment [60].

10. Non-Hodgkin Lymphoma

Non-Hodgkin lymphoma is a type of cancer that affects the lymphatic system, which is part of the immune system. NHL can develop in various parts of the body, including lymph nodes, bone marrow, and spleen. Early detection and accurate diagnosis of NHL are important for effective treatment. AI can assist in NHL diagnosis by analyzing medical images, such as computed tomography (CT) scans and magnetic resonance imaging (MRI) scans, as well as pathology samples. AI algorithms can be trained on large datasets of medical images and pathology samples to recognize patterns and detect signs of NHL [61]. Several studies have shown promising results in using AI for NHL diagnosis. For example, a study published in the journal "Nature Communications" in 2019 found that an AI algorithm trained on a dataset of over 20,000 lymphoma pathology images was able to accurately diagnose different subtypes of NHL with an accuracy of over 90%. Another study published in the journal "Blood Advances" in 2020 reported that an AI algorithm was able to predict the risk of relapse in patients with NHL with an accuracy of 84%. This could be useful in helping doctors develop personalized treatment plans for their patients. it's important to note that AI should not be used as a replacement for human medical professionals. Rather, it should be used as a tool to assist in diagnosis and improve accuracy. Any suspected NHL should be examined by a medical professional for proper diagnosis and treatment [62].

11. Pancreatic Cancer

Pancreatic cancer is a form of cancer that develops in the pancreas, a gland that creates enzymes and chemicals that aid in digestion and blood sugar regulation. Pancreatic cancer is frequently discovered at an advanced state, making treatment challenging. Early detection and precise diagnosis are critical for enhancing therapy outcomes. By analysing medical pictures such as computed tomography (CT) scans and magnetic resonance imaging (MRI) scans, as well as pathology samples, AI can help with pancreatic cancer detection [63]. To recognise trends and identify signs of pancreatic cancer, AI systems can be taught on huge databases of medical images and pathology samples. Several studies have shown encouraging outcomes when using AI to diagnose pancreatic cancer. For instance, consider research that was released. An AI system taught on a collection of more than 500 CT images, for instance, was able to correctly spot pancreatic cancer with a 91% success rate, according to 2019 research published in the journal "Clinical Cancer Research." An AI system was able to forecast the chance of pancreatic cancer recurrence after surgery with an accuracy of 81%, according to a 2020 research that was released in the journal "Annals of Oncology. It's crucial to remember though that artificial intelligence shouldn't be used in lieu of qualified human medical personnel. As an instrument to aid in diagnosis and increase precision, it ought to be used instead [64]. An expert medical examination is necessary for the correct detection and therapy of any suspected pancreatic cancer. Analyzing blood test results, such as CA 19-9 (cancer antigen 19-9) amounts, is an alternative strategy. Data analysis using AI systems can find anomalies that could be signs of pancreatic cancer. AI-assisted pancreatic cancer detection has the potential to increase diagnostic precision and efficacy while minimising the need for intrusive treatments like biopsies. It is crucial to remember that AI diagnosis should not be used in lieu of professional medical judgement and should only be used in collaboration with it. AI diagnosis has the potential to enhance the detection of pancreatic cancer and the effectiveness of therapy, but more study and confirmation are required before it can be extensively used in clinical practice [65].

12. Prostate Cancer

Prostate cancer is diagnosed through a biopsy, and the findings show how aggressive the disease is, indicating when to start therapy. The next stage of therapy entails a procedure called staging that centres on exams to gauge the severity of the illness. There may be a cure if the illness is discovered to be contained within the prostate capsule. The available therapies include [66]. Radical Prostatectomy: This surgical procedure completely removes the prostate organ and the prostate-box lymph nodes. This can be accomplished via open, endoscopic, or robotic surgery. Robot aided radical prostatectomy, which enables good functional recovery, is the finest surgical choice. Contrary to the widespread misconception that robots conduct robotic surgery, this robot is a master-slave device. Men frequently develop prostate cancer, and early detection is essential for effective therapy [67]. Prostate cancer detection and identification may be greatly aided by AI diagnostics. Prostate cancer can be detected using AI in a number of ways, including by analysing medical pictures such as MRI or ultrasound scans using machine learning techniques. The pictures can be analysed by these programmes to find patterns that suggest the existence of cancer. Analyzing blood test results, such as prostate-specific antigen (PSA) levels, is an additional strategy. Data can be examined by AI programmes to look for anomalies that might point to the existence of cancer. Prostate cancer detection by AI has the ability to increase diagnostic precision and effectiveness while also the necessity of intrusive treatments like biopsies. It is crucial to remember that AI diagnosis should not be used in lieu of professional medical judgement and should only be used in collaboration with it. Before it can be broadly adopted in clinical practice, more study and confirmation are required. AI detection has the potential to enhance prostate cancer identification and therapy results [68].

13. Thyroid Cancer

Using machine learning algorithms to analyse medical pictures, such as ultrasound scans, is one method of AI thyroid cancer detection. These programmes can examine the pictures to look for anomalies like nodules or tumours that might be cancerous [69]. Analyzing blood test results, such as thyroid stimulating hormone (TSH) amounts, is an additional strategy. Data can be examined by AI programmes to look for anomalies that might point to thyroid cancer. The use of artificial intelligence (AI) in thyroid cancer detection has the potential to increase diagnostic precision and effectiveness while minimising the need for pointless samples or operations. AI diagnosis should be used in combination with expert medical judgement and should not substitute it, it is crucial to highlight professional assessment and verdict. Before it can be broadly adopted in clinical practice, more study and confirmation are required. AI detection has the potential to enhance thyroid cancer identification and therapy results [70].

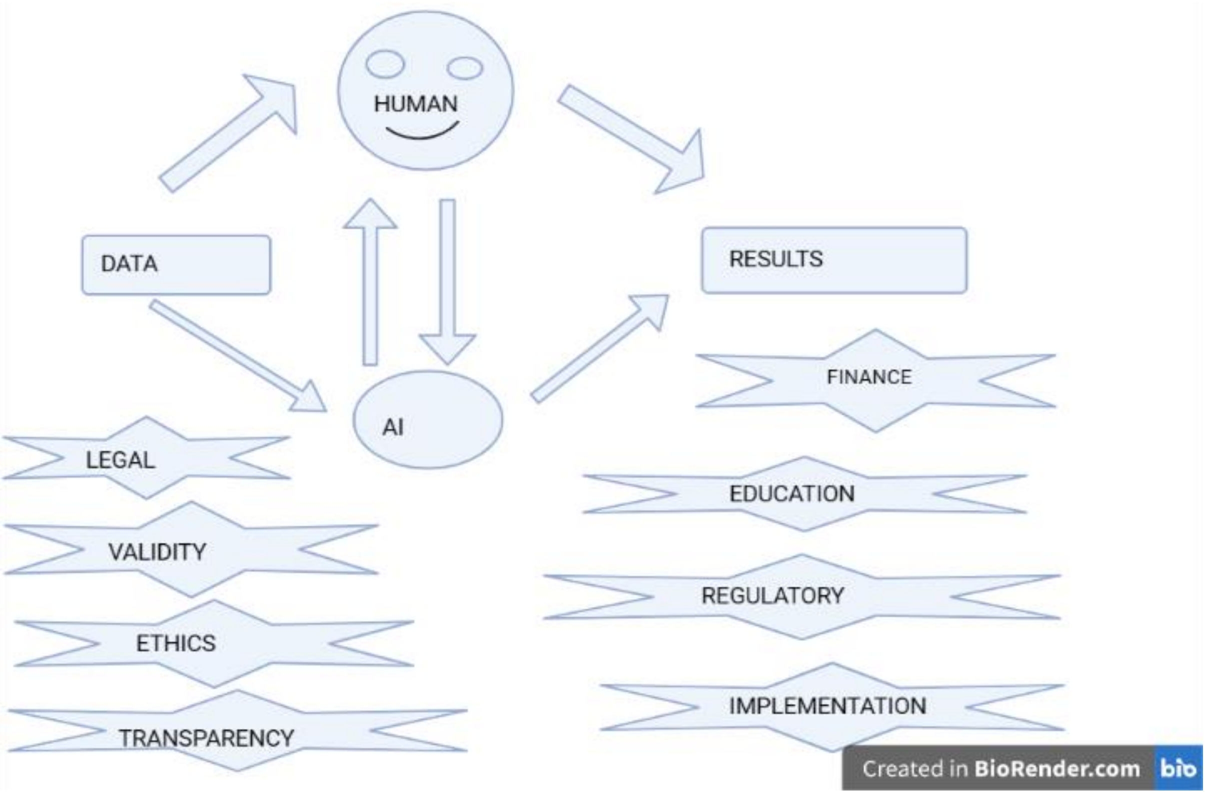

FIGURE 7: SHOWING THE RELATION BETWEEN AI (ARTIFICIAL INTELLIGENCE) AND HUMAN.

Conclusion

Artificial intelligence (AI) tools for cancer diagnosis are a quickly evolving area that has the ability to increase accuracy, speed, and personalised therapy choices for cancer patients. AI algorithms and models can analyse large quantities of medical imaging data and extract characteristics that human viewers may miss, resulting in more accurate diagnoses and personalised treatment plans. AI methods used in cancer detection include radiomics, texture analysis, and machine learning, to name a few [71]. AI tools are being created to analyse genomic data in addition to medical imaging, allowing for a better grasp of the hereditary variables that contribute to cancer formation and progression. This could contribute to more targeted and personalised therapy. While AI tools in cancer diagnosis are still in their early stages of development and implementation, there is significant promise for their use in clinical practice. However, it is important to note that AI tools should be used in conjunction with clinical expertise and not as a replacement for human decision-making [72]. Further research and validation of AI models and algorithms are needed to ensure their safety, efficacy, and integration into routine clinical practice [73]. The incorporation of AI tools into clinical practise has the potential to greatly improve cancer detection accuracy and speed, as well as allow more personalised treatment plans based on a patient's unique traits [74]. However, it is essential to highlight that AI tools should be used in conjunction with clinical assessment and decision-making rather than as a replacement for human knowledge and judgement. AI can assist physicians in detecting cancer early by analysing medical images such as X-rays, CT scans, and MRIs [75]. AI algorithms can be trained on huge datasets of medical pictures to recognise trends and make correct predictions. Artificial intelligence (AI) can assist physicians in personalising cancer therapy by analysing genetic data to anticipate how a patient will react to various treatments [76]. This can assist physicians in selecting the most effective therapy for each patient, thereby reducing side effects and increasing outcomes [77]. AI can help speed up drug development by analysing huge datasets of genomic and molecular data to find possible targets for novel cancer drugs [78]. Artificial intelligence (AI) can assist physicians in virtually watching cancer patients by analysing data from wearable devices such as fitness trackers [79].

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to me

Dear Dr. Gulshan Kumar,

This is with reference to an article entitled: "Role of Artificial Intelligence and Machine Learning in Cancer Diagnosis" which has been submitted for possible publication in Current Cancer Therapy Reviews, and in which you are listed as one of the co-authors.

The manuscript has been submitted to the journal by Swati Verma who is listed as the main author and who will be authorized to track the status of the paper after login.

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Thank you very much.

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