Original Article

Novel Artificial Intelligence Tool for Real-time Patient Identification to Prevent Misidentification in Health Care

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Abstract

Purpose: Errors in the identification of true patients in a health-care facility may result in the wrong dose or dosage being given to the wrong patient at the wrong site during radiotherapy sessions, radiopharmaceutical administration, radiological scans, etc. The aim of this article is to reduce the error in the identification of correct patients by implementation of the Python deep learning-based real-time patient identification program. **Materials and Methods:** The authors utilized and installed Anaconda Prompt (miniconda 3), Python (version 3.9.12), and Visual Studio Code (version 1.71.0) for the design of the patient identification program. In the field of view, the area of interest is merely face detection. The overall performance of the developed program is accomplished over three steps, namely image data collection, data transfer, and data analysis, respectively. The patient identification tool was developed using the OpenCV library for face recognition. **Results:** This program provides real-time patient identification information, together with the other preset parameters such as disease site, with a precision of 0.92%, recall rate of 0.80%, and specificity of 0.90%. Furthermore, the accuracy of the program was found to be 0.84%. The output of the in-house developed program as "Unknown" is provided if a patient's relative or an unknown person is found in restricted region. **Interpretation and Conclusions:** This Python-based program is beneficial for confirming the patient's identity, without manual interventions, just before therapy, administering medications, and starting other medical procedures, among other things, to prevent unintended medical and health-related complications that may arise as a result of misidentification.

Keywords: AI tools, incidence in radiotherapy, misidentification in health care, patient identification, Python

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Introduction

Radiation delivery accuracy and precision in cancer management have improved as a result of the significant advancements made in radiotherapy technology over the past few decades. Cancer is the second-most common cause of death worldwide, according to research from the World Health Organization. Cellular DNA mutations are the root cause of cancer.[1] One of the main objectives of these improvements has been to deliver radiation to the tumor volume while exposing the least amount of normal tissue to radiation.[2]

Recent decades have seen technological advancements in radiation therapy methods such as stereotactic radiosurgery, intensity-modulated radiation therapy, image-guided radiotherapy, and three-dimensional conformal radiotherapy.[3-12] Despite extensive digital and technological fusion, some radiation mishaps are still reported during the delivery of radiation, albeit on a very infrequent basis.[13]

In fact, the fundamental tenet of the strategy is to "minimize radiation exposure to normal tissue," which encompasses not only the exposure of normal cells during radiotherapy but also any additional exposure, such as accidental or incidental exposures. Over the course of more than 100 years of radiation applications, numerous radiation exposure occurrences have been documented. Many examples of unintentional radiation exposure have been documented, mostly by Western peers, but

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it is possible that similar incidents may occur in other regions of the world. Not only in external-beam therapy and unsealed source therapy, but also in nuclear medicine and radiodiagnosis, mistakes in patient identification have occurred frequently.[14] This is not just restricted to radiotherapy; it can also occur when administering radiopharmaceuticals and chemotherapy to the incorrect individuals as a result of a mistake in patient identification. Human error, which may occur during registration and the creation of a bar-coded slip at busy registration counters, can result in identification errors that are made carelessly and unknowingly, the patient's misidentification is crucial at every stage of the health-care process.[15] All specialties should consider this, but some are more sensitive than others for specific reasons, such as when administering chemotherapy drugs.[16] This could be the main reason for a number of problems with how patients move through the health-care system, from their initial visit through their discharge. Patient visits for drug administration under the expert care teams and specialists should be between 6 and 10. Due to their cytotoxic nature and individualized preparation, these medications may cause complications if given to the incorrect patient or at the incorrect dosage. In the event of a facility that administers chemotherapy drugs and in a manner similar to other specialties such as pathology, transfusion medicine, and laboratory medicine, various instances of patient misidentification have been documented in the past despite the presence of numerous technological interventions.[17] These cases involved the wrong patients, unintentional exposure to the attendant helping the patients while they were left in the treatment room. Technology-based interventions, such as LMOS, door interlocking, and CCTV, have occasionally been developed in their place to prevent the occurrence of such instances to address this issue with the idea that even no single individual obtains inadvertent exposure.

Nowadays, advanced LINAC is coming with the feature to display of photo of the patient on the Linear Accelerator (LINAC) gantry once it is selected/taken up for the treatment at the console subject to the photo submitted at the time of registration/simulation for the radiotherapy. In the modern era of technology, expensive and high-cast investment auto face recognition systems are commercially available, however, their deployment is still very limited primarily due to high cast and reluctant approach toward the rare and significant event if happens, at least for an individual.[18]

In this study, authors developed a Python data science-based real-time patient identification program that can be freely accessed and used in health-care facilities such as radiotherapy, chemotherapy, radiodiagnosis, nuclear medicine, transfusion medicine, pathology sample collection, or any other medical procedures that may have the potential for misidentification problems.

Causes of radiological incidence in radiotherapy

The radiological accident is defined by the basic safety standard as "any severe unintended event, including an operating error, equipment failure, or other mishap, the consequences of which cannot be ignored from the protection or safety point of view, and which usually leads to potential overexposure or to abnormal exposure conditions for treated patients, staff, or the general public."[19] "Accidental exposure" is defined as "individuals exposed as a result of an accident, other than emergency personnel."[20] According to the definition, a radiological event during radiation therapy could harm patients, the general public, or employees.

Radiological incidents in radiotherapy can arise from multiple factors, each contributing to potential risks in patient care and treatment outcomes. Human error during simulation, where inaccuracies in patient positioning or treatment planning can occur, also poses a notable risk. Issues related to the commissioning of treatment planning systems can introduce errors into the treatment process. This includes miscalibrations, inaccuracies in dose calculations, and errors in the anatomical site(s) to be treated. In addition, inadequate review of the patient's chart and miscommunication among health-care professionals may lead to incorrect treatment delivery. Leakage radiation from accelerators, malfunction of accelerators, and treatment unit mechanical failures are technical aspects that contribute to radiological incidents. Accelerator control software errors, errors in the calibration of Co-60 sources, and transcription errors of the prescribed dose can further compromise the safety and efficacy of radiation therapy. Errors during the initial stages of treatment, such as using the wrong tattoo mark to identify the treatment area or placing treatment marks incorrectly on the patient's body, highlight the importance of precision in the setup process and may also result in radiological incidences. Furthermore, mistakes in the selection of treatment modality, computer programming entries, and formula errors in treatment planning computers can introduce systemic vulnerabilities. Human factors play a significant role in radiological incidents, including misreading treatment time or monitor units by technologists and errors during the actual treatment process. In conclusion, a thorough understanding of the diverse causes of radiological incidents in external beam therapy is imperative for implementing robust quality assurance protocols. Identifying and understanding these causes is crucial for implementing effective preventive measures and ensuring the safety of patients undergoing radiation therapy. One significant cause of radiological incidents is the error in identifying the correct patients. This may occur during various stages of the treatment process, from patient admission to the final session of treatment, i.e., radiation delivery. However, including other reasons, the probability of misidentification in radiotherapy becomes manyfold as radiation therapy is delivered over multiple seasons (i.e., fractions) unlike surgery and other treatment modalities.

Python program in the development of patient identification tool: A brief description

To solve the problem of patient misidentification in health-care facilities, as discussed above, the authors introduced a novel patient identification tool using the Python program. Originally created by Guido van Rossum, the Python program is a potent, high-level, scripting, interpreted, open-source language and is publicly accessible.[21,22] It is compatible with a variety of operating systems, including Windows, Linux, and Mac OS. Python may be used to create a variety of programs, including those for systems, databases, component integrity, networks, the Internet, graphical user interfaces, games, and robotics.[23] Python has been rated as the top programming language in 2022 by the popularity of programming language.[24] Pickle (Python), PyEphem, Pygame, Pyglet, PyGObject, PyGTK, PyObjC, PyQt, PySide, Pandas, NumPy, Python Imaging Library, and Natural Language Toolkit are just a few of the many standard libraries available for Python. Python has a large library system, therefore, no unique code needs to be developed. Python offers amazing qualities, such as being straightforward and simple to learn. Without compiling the complete program, Python code can be run line by line. Python's status as an interpreted programming language is made clear. Python is a very expandable language since code may be written in other languages such as C and C++.[25,26]

Python is used in scientific research for things such as conducting participant-based experiments, organizing and processing data, and doing statistical analysis and data visualization. Python is a current general-purpose programming language that has applications in scientific and mathematical modules and is well-liked in scientific computing for its understandable syntax.

Materials and Methods

The authors utilized and installed Anaconda Prompt (miniconda 3), Python (version 3.9.12), and Visual Studio Code (version 1.71.0) to create Python environment in the system for the design of the patient identification tool based on the Python program. During patient data identification, this program omits all the anatomical views except the face. In the field of view (FOV), the area of interest is merely face detection.

In the current study, Python is used in face identification by utilizing libraries such as OpenCV and face recognition to detect and recognize facial features, process images, and implement machine learning algorithms for identification using the Haar Cascade classifier. These classifiers are then combined into one strong classifier that can accurately distinguish between samples that contain a human face from those that do not. The Haar Cascade classifier that is built into OpenCV has already been trained on a large dataset of human faces, so no further training is required. Authors just needed to load the classifier from the library and use it to perform face detection on an input image.[27] Initially, the OpenCV library has been installed using command prompt by simply run the following command "pip install OpenCV-python." This code downloads and installs the OpenCV library for Python using the command prompt which is pip package manager. Pip is a package installer for Python and is used to install and manage software packages written in Python. The OpenCV library, which is a popular computer vision library, was used for image and video processing.

In the present study, the patient identification program was developed in two versions. Version 1.0 is extremely capable of detecting the patient in real-time as soon as one comes within FOV of the camera (within 1 m distance from the camera) attached with the developed in-house program. In the case of radiotherapy facility, the camera could be deployed in the control console/maze wall area at an appropriate place and height so that the patient face can be detected by the camera without any human manual intervention while the patient is walking freely inside the treatment room.

It also has a function to identify any other individuals participating in the treatment, such as the patient's family members. In version 1.0, if the patient moves away from the camera, the algorithm will not gather any information till detected another patient and the already collected information would not appear on the screen. In version 1.0, only live data are displayed. Both versions have the advantage of detecting the patient within a 1-m range; therefore, no occupational workers would be detected who are just beyond that distance in the treatment room. Version 2.0 and version 1.0 are nearly identical in terms of their attributes. Over version 1.0, version 2.0 has a few additional features. Until another patient is spotted within FOV, the earlier identified patient's data would be frozen out on the screen. Version 2.0 is built in such a way that there is a 10-s gap between patient data that has already been discovered and data that still needs to be identified to examine the correctness of patient data identification. In corresponding to both versions, this program omits all the anatomical views except the face. In the FOV, the area of interest is merely face detection.

The overall performance of the developed program is accomplished over three steps, namely image data collection, data transfer, and data analysis, respectively, as shown in Figure 1.

Step 1

During the simulation, patient imaging data must be gathered. Using a simulation technique, a Python program has been developed that can gather patient photos in just 10–30 s. Twenty photos are gathered by this program within 20 s. As shown in Figure 2, the gathered photographs are automatically stored in an individual folder created for each of the patient. Data gathering from the particular folder makes it easy because images are kept in a folder with patient names.

Step 2

Data transfer is the second phase in our method, which is really straightforward. Once the image data have been gathered, it is time to process it and extract the necessary information. As shown in Figure 3, the data then moves to the desired folder.

Step 3

The authors made another program specifically designed to analyze the patient who is really in the treatment room in real time for step 3. The patient's name accompanied with the treatment/cancer site is revealed when the program compares the data from a targeted folder to the genuine patient who is actually present in the treatment room. Versions 1.0 and 2.0 of this program are available based on user preference. The interphase Python program is depicted in Figure 4.

Performance analysis of developed face identification program

To evaluate the performance of the face identification program of both version 1.0 and 2.0, a total of 25 individuals were enrolled as shown in the table no 2. First, similar to the intended scenario, photos of each of the individuals were taken and saved in the target folder. Then, each of the volunteers was asked to move exactly in a similar way as the real patient approach toward the camera attached with developed face identification program. The findings and results of the program were recoded in terms of true positive (TP), false positive (FP), false negative (FN), and true negative (TN).

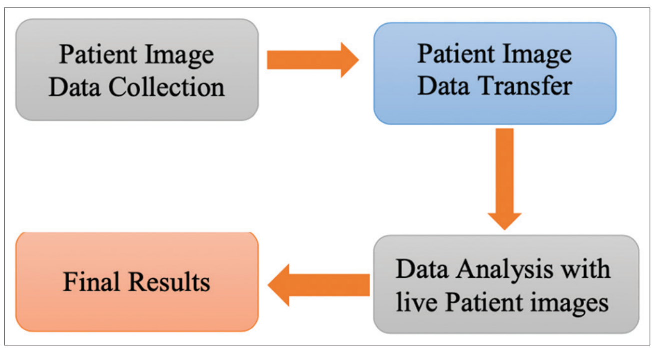

Figure 1: Patient identification program workflow

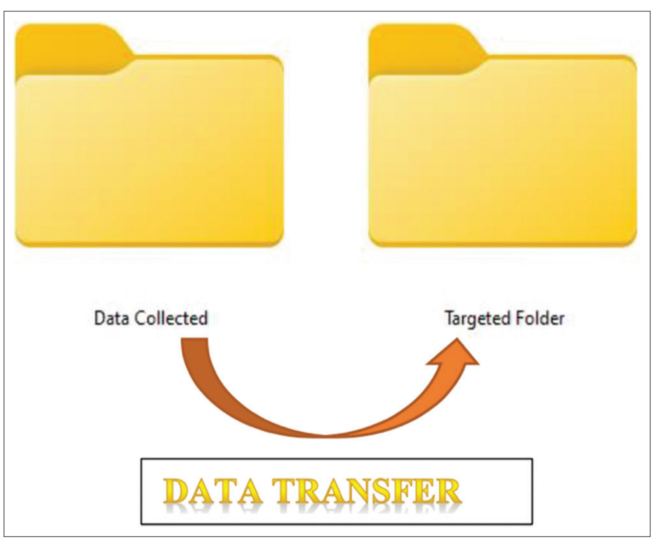

Figure 3: Data transfer

Statistical assessment of face identification program

Statistical parameters,[28] as given below in equations, (1–4) for the performance assessment of the developed face identification program were calculated using the data from Table 1.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (1)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (2)$$

$$\text{Specificity} = \frac{TN}{TN + FP} \quad (3)$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FN + FP} \quad (4)$$

A separate in-house Python program was created for the calculation of the statistical parameters, i.e., precision, recall, specificity, and accuracy as mentioned in equation (1–4) as written below.

```
def calculate_metrics (tp, fp, fn, tn):
# Calculate precision
precision = tp / (tp + fp) if (tp + fp) ! = 0 else 0

# Calculate recall
recall = tp / (tp + fn) if (tp + fn) ! = 0 else 0

# Calculate specificity
specificity = tn / (tn + fp) if (tn + fp) ! = 0 else 0

# Calculate accuracy
accuracy = (tp + tn) / (tp + fp + fn + tn) if (tp + fp + fn + tn)
! = 0 else
return precision, recall, specificity, accuracy
```

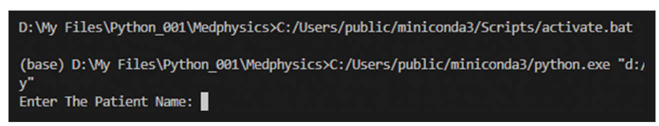

Figure 2: Program asking for patient name to store patient data in targeted folder

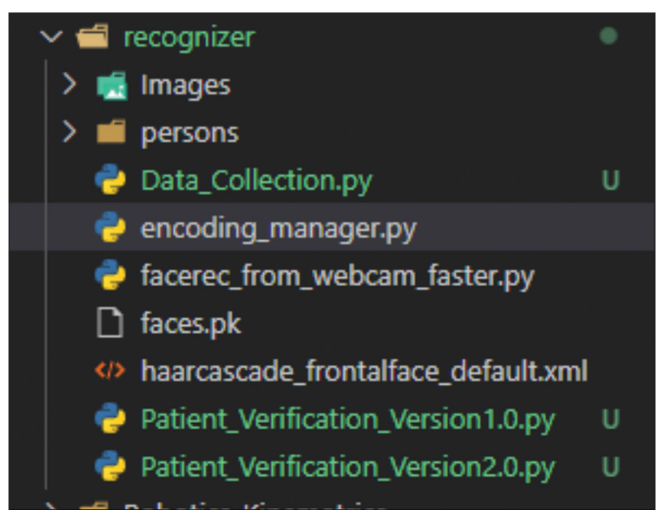

Figure 4: Program database

Table 1: Confusion matrix

Predicted values	Actual values	
	Positive	Negative
Positive	TP (A)	FP (B)
Negative	FN (C)	TN (D)

TP: True positive, FP: False positive, FN: False negative, TN: True negative

```
# Collected data from observation table: Input data for Metric calculation
tp = A
fp = B
fn = C
tn = D
precision, recall, specificity, accuracy = calculate_metrics (tp, fp, fn, tn)
# Print confusion matrix
print("Confusion Matrix:")
print(f"True Positive (TP): {tp}")
print(f"False Positive (FP): {fp}")
print(f"False Negative (FN): {fn}")
print(f"True Negative (TN): {tn}\n")

# Print calculated metrics
print("Metrics:")
print(f"Precision: {precision:.2f}")
print(f"Recall: {recall:.2f}")
print(f"Specificity: {specificity:.2f}")
print(f"Accuracy: {accuracy:.2f}")
```

Results

The developed programs produced a variety of helpful consequences, including:

Identifying unknown person

This program provides site name and patient identity details. Radiation practice takes place in dedicated facilities called radiation treatment rooms. The program will output "Unknown" if a patient's relative or an unknown person is found in a restricted region of 1-m distance. As illustrated in Figure 5, these phenomena can be accomplished through versions 1.0 and 2.0, respectively.

Real-time identification with simultaneous multiple results

Results are provided for both a single patient and groups of patients who are present in the treatment room and within a 1-m radius of the detecting camera. If a group of patients enters a treatment room, this program will identify everyone in the room, including those whose identities are unknown. As shown in figure 5, the version 1.0 program provides real-time patient identification data, however, the resulting data vanishes as soon as the patient travels away from the camera. The patient data cannot be stored on the screen in version 1.0.

In Figure 6, "ABC" represents the patient's name and "SN" represents the site name, respectively.

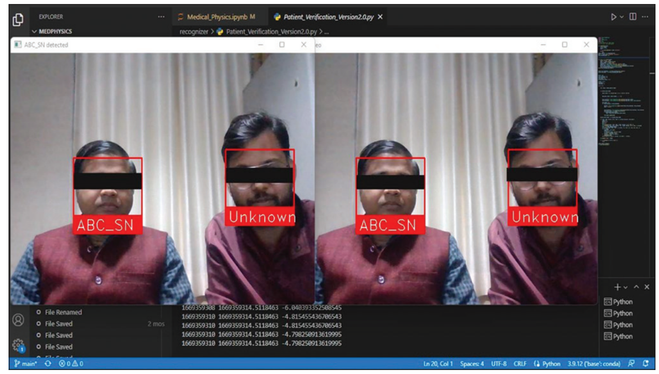

Figure 5: Real-time patient identification with unknown identity

Dead time in between two results

There is a minimum waiting period of 10 s before providing another result, which is referred as "Dead Time." When the patient's photograph is recognized, two windows in the program will launch. One of the windows shows real-time imaging data, while another window remains frozen until it recognizes data from a different patient. As shown in Figure 7, the frozen window would not record another patient until dead time has passed. This feature is facilitated in version 2.0 only.

In Figure 7, "XYZ" stands for the patient's name while "SN" stands for the site name.

Program calculated result is given below:

Confusion matrix

The qualitative performance assessment of in-house developed face identification program was quantified in terms of statistical parameters. The result of the face identification program was recorded with a precision rate of 0.92, recall rate of 0.80, and specificity rate of 0.90. Apart from these, the accuracy of the program was found to be 0.84.

Discussion

In the present study, the authors designed an AI tool aimed at preventing misidentification within the health-care system. Following the validation of the algorithm, it was found that the recall rate and accuracy were 80% and 84%, respectively. To enhance both the recall and accuracy of the developed algorithm, two key measures should be considered. The identification of true-negative results is crucial. This can be achieved by paying attention to certain factors during data collection and analysis. Specifically, it is recommended to avoid the use of spectacles during these processes for optimal results. In addition, ensuring an adequate amount of light during the application of the identification tool is essential to obtain accurate results. By carefully considering these aspects, the algorithm's performance can be further optimized.

Walt Bogdanich conducted a case study in New York in 2010 titled "Case Studies: When Medical Radiation Goes Awry" that focused on the monitoring of radiotherapy and gathering error

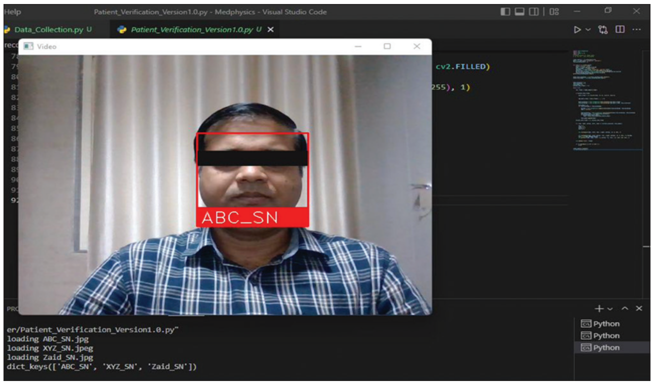

Figure 6: Real-time patient identification version 1.0

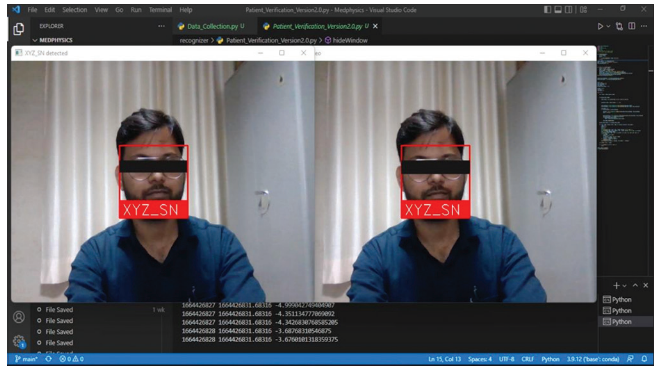

Figure 7: Real-time patient identification version 2.0

Table 2: Outcome of face identification program using the developed program

Samples	Observed model result	Outcome
Sample 1	Correct	TP
Sample 2	Correct	TP
Sample 3	Correct	TP
Sample 4	Wrong	FN
Sample 5	Correct	TP
Sample 6	Correct	TP
Sample 7	Wrong	FN
Sample 8	Correct	TN
Sample 9	Correct	TP
Sample 10	Correct	TP
Sample 11	Correct	TN
Sample 12	Wrong	FN
Sample 13	Wrong	FP
Sample 14	Correct	TP
Sample 15	Correct	TP
Sample 16	Correct	TP
Sample 17	Correct	TP
Sample 18	Correct	TN
Sample 19	Correct	TN
Sample 20	Correct	TP
Sample 21	Correct	TN
Sample 22	Correct	TN
Sample 23	Correct	TN
Sample 24	Correct	TN
Sample 25	Correct	TN

TP: True positive, FP: False positive, FN: False negative, TN: True negative

data. In addition, they spent months gathering and evaluating records as well as looking at accident patterns there. Records, therefore, list 621 errors and 18 accidents that represent various medical errors.[29]

The following are a few of them:

- Wrong patient receives treatment due to the misidentification of the patient
- Dose calculation error results in higher dose of radiation
- Radioactive seeds measured incorrectly
- Alternate day treatment mistake by radiation therapist
- Some extra fractions result in radiation overdoses
- Old photos result in the wrong body part being radiated
- Computer error not observed
- Missed to check the radiation dose
- Radioactive seeds implanted in not targeted volume
- Temporary workers were unaware of routine work resulting in a patient's overdose
- The computer is overridden, and the result in the wrong body part is radiated
- The wrong radiation dose is administered to the patient by the staff
- Therapist overrides the interlock
- Misidentified prostate glands
- Radiation therapist random errors result in radiation overdose.

The Joint Commission established its program for National Patient Safety Goals in 2002. The improvement of patient identification accuracy is the program's top priority. Later, to lower the risk of chemotherapy errors, the American Society of Clinical Oncology and the Oncology Nursing Society worked together to develop chemotherapy administration safety standards. To implement best practices in cancer care, this program will re-verify patient identity information. Even though some protocols have been followed, patient identification mistakes still happen. Therefore, it may be said that to lower the chance of error, at least two patient identities are necessary. One question persists despite all of the efforts and protocols: "Why patient identification errors continue to occur in the cancer care department?"[30] In 2001, the Radiation Oncology Safety Information System (ROSIS) was established. The ROSIS analysed a total of 1074 reports in which 97.7% are related to external beam radiation treatment and 50% found to be under incorrect irradiation. Out of these events, many incidents arises during treatment, but they are not detected prior to treatment.[31] We have created a Python program that will serve as one of the patient identification tools and help to increase the accuracy of patient identification. This program can be used again for deep learning Python programs to verify patient identity when they are under a lot of workload. This Python program can be helpful in a variety of fields, including brachytherapy, radiotherapy, chemotherapy, and nuclear medicine.

The fact that radiation administration is a noninvasive kind of treatment which cannot be seen or felt even during irradiation neither by the patient nor by operators may be one of the major causes of mistakes in radiation delivery, such as irradiating the incorrect place or the incorrect patient and failing to notice and report them. According to the authors' knowledge, nearly half to two-thirds of cancer patients received this modality during their medical therapy, but neither during the course of the treatment nor just after it did it create any effects and hence do not come in the notice, like an adverse reaction after administration of wrong drug with severe side effects. Probably, this is one of the major reasons that these mistakes in the erroneous delivery are not reported, this becomes rare especially when they include patients and attendants who lack education. In addition, radiotherapy requires frequent visits from the patient and their attendants to the operators; for these reasons, even when the patient and their attendants are aware of mistakes in handling, they are reluctant to bring them to the attention of the administration or a higher level of authority as they are afraid of noncooperation and proper response during their next visit. However, when working to reduce errors in the administration of radiotherapy, chemotherapy, and radiopharmaceuticals, accidental human (manual) errors caused by a heavy patient load, long shifts, and anxiety, among other factors, may also be important to take into account.

The use of technology and digital innovations has significantly increased safety and ease in a number of different industries, including telemedicine, rail travel, and aviation. The authors attempted to develop a Python-based program that could be easily run in one of the already available computer systems without large capital investment like in the case of other accessories. The authors were motivated by the application of digital technologies with applications in other sectors and saw the role of the same in accurate and correct delivery in health-care facilities, primarily in the case of radiotherapy, chemotherapy, and radiopharmaceuticals. One may need a digital camera to be attached to the computer system and start using.

Way forward

The information gathered from this programming can be utilized to establish a national repository dataset of different types of diseases, such as the patients of cancer patients, which will contain the patient's name, treatment site, and photographs. This information can be used by national governments for a variety of purposes, such as tracking the number of cancer patients treated in a given year, and demography, which may be helpful in define the statistics for the country's disease-wise data for analysis and visualization. Even departmental patient attendance can be possible; at the advanced level of attendance, which includes patient treatment room in-time and patient treatment room out-time.

Conclusions

The use of artificial intelligence and machine learning in radiation facilities has benefited fortunes throughout time. When patients have identical identity parameters, it can be utilized as a patient verification system at radiation installation sites, radiopharmaceutical drug administration, radiology, pathological specimen collection sites, and blood transfusion/collection sites to assist in reduction of inadvertent exposure and problems due to errors in identification.

Availability of source code

The AI tool used in the present study for the real time patient identification can be accessed at https://github.com/RGBRAND/Patient-Identification-System which is free for intended use subject to the citation of this article when findings are published.

Declaration of patient consent

The authors certify that they have obtained all appropriate participant consent forms. In the form the patient(s) has/have given his/her/their consent for his/her/their images and other clinical information to be reported in the journal. The patients understand that their names and initials will not be published and due efforts will be made to conceal their identity, but anonymity cannot be guaranteed.

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Nil.

Conflicts of interest

There are no conflicts of interest.

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