Mitigating Pancreatic Cancer through Data-Driven AI Techniques, Holistic Health Record, iHELP and Integrative Systems

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Abstract

Artificial intelligence (AI) continuously revolutionises various spheres of life. It is high time AI got well integrated into the health sector of all nations. Doing so would proffer tangible solutions to various health challenges. This study is informed by the need to find lasting or optimised solutions to cancers as well as other chronic health challenges. It posits that the increasing spate of cancer in contemporary times can be mitigated significantly through momentous integration of data-driven AI techniques, holistic health record (HHR), iHELP and integrative systems. It demonstrates that the integration of the aforementioned system enhances effective analysis and interpretation of complex data; provides a competitive edge in decisions on cancer and other health challenges; and allows for greater precision, efficiency, foresight, increased innovations, and informed strategies for mitigating pancreatic cancer and other types. The study concludes that cancer and other cardiovascular diseases can be reduced to the barest minimum through meaningful application of data-driven AI techniques, such as machine learning, deep learning, internet of things, HHR, and the proposed iHELP systems to medical practices capable of combating pancreatic cancer and other cardiovascular diseases. The study calls on stakeholders to ensure increased adoption of data-driven and integrative systems for the optimisation of healthcare services on pancreatic cancer, and for the attainment of best practices in the healthcare sector. Researchers are charged to variously investigate the subject matter of this present research and related ones for betterment and more discoveries.

Keywords: *Mitigating, Cancer, Data-driven, AI techniques, Integrative systems*

Introduction

Cardiovascular diseases destroy the majority of Europeans as well as people of other nations of the globe. Cancer is the second most deadly cardiovascular diseases. To that end, this article discusses the dire need for designing comprehensively integrated technological measures for addressing the decried health concerns. It argues that in addition to traditional medical systems in healthcare facilities, healthcare centres and health organisations, emerging ICT services that harvest massive amounts of data about one's health can help better in tackling the raised health concerns and even many other health challenges. According to the World Health Organization, a strong approach to integrating data should consider more than just a person's medical history. These include their age, social and bodily characteristics, genetics, family and friend network, and their interactions with these people.

Such ICT services include those that use IoT devices, sensors and mobile apps for disease tracking or decision assistance. These instruments can help create decision-support tools like individualized early risk prediction, prevention, and intervention help improve medical personnel's proficiency by enhancing their understanding of diseases and how to interpret their symptoms and effects. These technology-based systems and services can handle the difficulty of offering multidimensional analytic insights on integrated data while extracting value for healthcare stakeholders. The article posits that simultaneously, advanced data exploitation tools should use artificial intelligence (AI) to gain insights from complicated integrated data. Machine learning, deep computing and system neuroscience regarding AI can be applied to develop robust selection assistance systems that predict risks from various characteristics, including food, age, gender, lifestyle, environment, and genetics.

Cancer Prevalence

According to the WHO, cancer is Europe's number two cause of fatality and morbidity, with 3.7 million new cases and 1.9 million deaths annually [1]. Cancer of the pancreas (PC), with a higher incidence in developed nations, ranks seventh among all forms of cancer in terms of cancer-related fatalities on a global scale. The estimated 495,773 reported cases and 466,003 deaths (4.7% of all cancer-related deaths) in 2020. According to projections given by GLOBOCAN, pancreatic cancer was ranked the fourteenth most prevalent cancer globally [2]. Pancreatic cancer was also the EU's fourth greatest cancer killer in 2018 [3]. Western Europe had the greatest death rate, being 7.6 per 100,000 inhabitants, in that year. This is preceded by the key and Eastern European Union (7.3), the region of North America (6.5) each [4].

With 52.3% of all deaths from pancreatic cancer occurring in developed nations, the majority of these deaths were caused by the disease [5]. Furthermore, pancreatic cancer is more frequent in men and causes more deaths with age [6].The inadequate global survival estimate for malignancy in the pancreas, of approximately 5%, is a significant factor in the decision to combat this specific form of cancer. The elevated frequency and fatality rate indicate the need for prompt risk evaluation and identification that can reduce mortality. In addition, specific preventive and intervention strategies, such as early screening initiatives for people at high risk, can save lives. Early-stage pancreatic cancer typically shows no outward symptoms. Unspecific symptoms include weight loss, jaundice, pruritus, light-coloured faeces, discomfort in the stomach, and weariness as the tumour increases.

Symptoms like anorexia, early satiety, nausea, dyspepsia, and others can indicate many illnesses [7]. The diagnostic power of MDCT, MRI and endoscopic techniques for diagnosing pancreatic cancer is restricted. Screening methods have hitherto focused on pre-invasive cancers rather than early PCI. Medical specialists claim that proactively assessing and reducing risks can lower the chance of getting cancer. Invasive pancreatic cancer can quickly spread outside the pancreas, thereby limiting its diagnostic relevance. These factors emphasize early and individualized prevention. Primary sickness prevention requires considering the cause, and disclosing risk factors that may identify high-risk individuals.

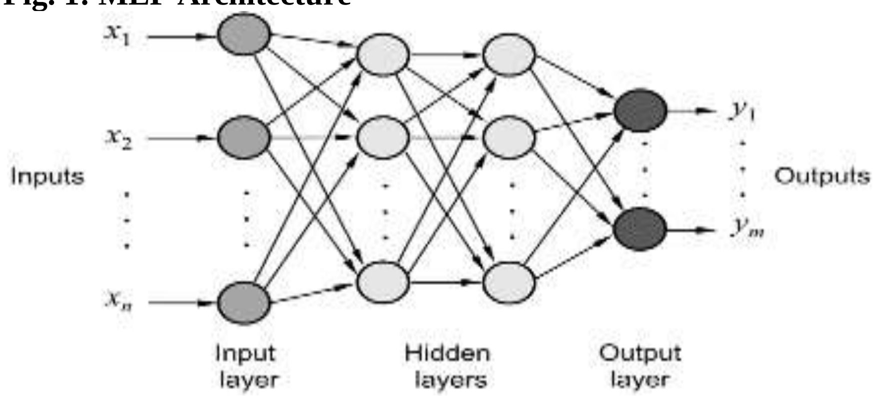
One of the best ways to lower one's risk of getting cancer of the pancreas is to change the associated risks that you can control, such as your lifestyle, behaviors, and social interactions. For example, you could reduce smoking, drinking, and red meat, eat more fruits and vegetables, and exercise regularly. Successful investigation and deductive reasoning of each of these facts are crucial to assessing their potential to reduce disease risks [8]. These autonomous systems limit the benefits of data integration. Healthcare personnel cannot deliver person- and disease-centered health monitoring, risk prediction, prevention, and personalised therapies, because systems and data are not integrated well enough and technology is not integrated well enough. To overcome these obstacles, a strong strategy for data integration and sophisticated instruments for data exploitation is needed.

How Artificial Intelligence Addresses Health-Related Problems

AI can translate and analyse examinations thirty-fold faster and with 99% accuracy, which eliminates the need for pointless biopsies [9]. The use of AI, via portable and mobile applications, can help to raise enhanced health knowledge, early identification, and tracking of wellness and health-related problems [10]–[12]. Giving more precise answers to the right individuals at the right time is made possible by the second option.

Also, the accessibility of cutting-edge wearables and Smartphone apps offers a convenient means of delivering AI-powered personalized early risk assessment and decision support, with reference to preventive and intervention measures. Using cutting-edge user profiling techniques will provide patients individualized counsel and a personalized way to get it easier, increasing, encouraging and evolving patient compliance. See the following Figure 1:

Fig. 1: MLP Architecture



Source: Authors, 2022

Using linked data and AI tools for healthcare services is a good idea that practitioners and policy-makers have to consider and adopt accordingly. They ought to facilitate the development of standards or recommendations. The difficulty is not only to combine and analyze data from several sources, but also to present diverse analytical perspectives for the good of citizens, doctors, and policy-makers. More so, AI-HA integrates holistic health data with AI to research on pancreatic cancer, with a focus on early risk detection and personalized prevention and intervention measures through technology, would huge positive results. This study anticipates the following:

- Effective image segmentation and classification approach proposed to identify the pancreatic cancer region by applying deep learning and improvising the diagnosis process among the patients with proper treatment.
- Modified RF based CNN, with improved local feature information for medical imaging classification to perform pancreatic cancer diagnosis.
- Image pixel extraction with resonance imaging to perform image segmentation for pancreatic cancer cell detection using deep learning, neural networks and automated detection pancreatic cancer.

Another area, where holistic health data and AI converge, is the analysis of the implications of certain preventative actions and therapies. The latter will offer fresh perspectives on the psychological facets of the illness. Furthermore, the development of preventative measures and interventions within these environments will target high-risk individuals to lower their chance of acquiring pancreatic cancer.

Standardised Data Integration, AI and Solutions to Health-Related Problems

Standardised data integration, learning model updates, and analytics are important facets and obstacles of contemporary eHealth systems. Ambient Assisted Living (AAL) systems, which offer user-friendly interfaces and assistance features, are the product of ambitious R&D endeavours. Integrated techniques have not been able to lower entry barriers in the healthcare industry. So, researchers are looking for innovative components that can lead to new end-user experiences and services. The following two cutting-edge methods for addressing these problems established the standard for creating and applying the iHELP platform and method. The global open-source IoT platform [13] enables interoperability and quick IoT solution development. With these, customers can customise their experience and way of life increases and speeds up the potential for interconnectivity.

The fast expansion of the AAL IoT universe means that regular updates to linked systems bring new features and applications, thereby providing the middleware platform with limitless possibilities. Intelligent products and services can instantly interact, opening up endless possibilities for the Internet of Things. The latter illustrates the growing necessity for establishing entirely new living platforms and surroundings in the modern healthcare industry, where consumers can easily exchange important data between systems and devices. The ideas are intersected by the eWALL platform [14]. Like AAL, eWALL is using ICT to develop ELEs to foster independent living. These are enclosed spaces that provide older individuals with support in daily living. The purpose of eWALL is to help make up for age-related physical limitations, prolonging functional capacity, delaying institutionalization, increasing autonomy, and QoL improvement.

A modular cloud-based platform is a component of eWALL, a wall-mounted system. The platform can integrate off-the-shelf and custom devices and a supporting Sensing Environment in the primary user's home that interacts with the primary user. Both conceptual entities make up a eWALL system. The entities are the Home Environment and the Cloud Environment components. Patients' residences host the system's sensing components, the eWALL Home Environment. All sensing capabilities are contained within market-available off-the-shelf devices. Integrating various devices into the eWALL Cloud Environment transparently and seamlessly is the responsibility of the Device Gateway (GW). The "Processing component" is tasked with expediting the interpretation of sensing data to perform critical functions, such as fall detection, presence detection, etc. The "Home DB" temporarily stores patient data before moving it to the "Cloud DB" for long-term preservation. All patient data collected from patients' homes is hosted and analyzed by the eWALL Cloud Environment. The system is characterised by connectivity gateways, notification capability, reasoning capability, and application integration.

Harmonizing and integrating data holistically is another crucial component. With this component, holistic harmonisation and integration of data across many data stores and locations obtain easily. To that end, electronic health records (EHRs) make it easier to handle patient information for use in healthcare and other contexts across institutional, geographic, and national boundaries [15]. The results include:

- ❖ Better data exchange
- ❖ Optimised and reliable storage, processing, and analysis
- ❖ Improved quality control, disease surveillance, public health monitoring, and trend analysis.

Data models must be standardised to ensure interoperability across all medical information systems that store patient clinical data. Although various standards enable organised clinical material sharing [17-19], organisations often employ alternative standards. Therefore, standardised security and data exchange models are necessary. A lot of efforts are being directed toward standard system architectures to give various stakeholders uniform access and data-sharing models. More standardised data-sharing models must be developed to link RTD initiatives across the lifetime of health and employ shared knowledge to benefit stakeholders.

Consequently, the CrowdHEALTH project, specifically the HHRs, suggest a comprehensive method for incorporating all health variables into novel frameworks [19]. A patient's behavioural information, healthcare information, results of laboratory tests, information gathered from interested parties, information about social contacts, and biological and behavioural information gathered from medical equipment and sensors are all possible inclusions in a Holistic Health Record (HHR). HHRs comprise customized data from healthcare systems and citizen-specific data, including age, ethnicity, gender, lifestyle, fitness/wellness, diet, and other health data.

Modified Prediction Model

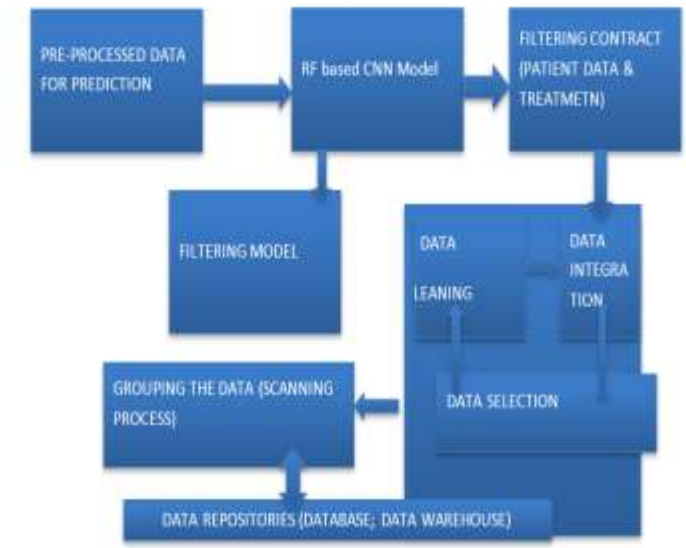
Artificial intelligence (AI) has many advantages over arithmetic and statistical analysis. AI algorithms have shown promise in performing healthcare jobs, such as identifying diseases faster and more correctly than human beings [20]–[25]. Additionally, machine learning techniques have been used to precisely measure delivery [26]. Unfortunately, standard supervised learning methods are not great at finding risks early or analysing new conditions for which there is no enough training data [27]. On the other hand, they are good at helping people make more accurate decisions. In iHELP, more cost-effective unsupervised learning algorithms detect early risks and analyse pancreatic cancer risk variables based on patient clinical records.

Such records include profile, diagnosis, comorbidity and medication. The investigation will identify dangers, contributing variables, and projections like pancreatic cancer risk factors. The analytical function results will be used to determine which individuals or prospects are most likely to experience the indicated hazard and who exhibit a tendency towards characteristics related to pancreatic cancer risks. In addition, iHELP aims to collect, handle and evaluate lifestyle data. This kind of data, lifestyle data, is also regarded as secondary data. Thus, particular and individualised preventive actions and treatments must be developed based on the study of known patient populations and these recommendations will be customised to each patient's needs and grouped based on their psychological profiles to guarantee adherence, acceptance, and ongoing usage of the tracking and guidance tools.

The recommendations are additional to the chance for success distribution methods, being wearable and mobile apps. IoT technology, handheld devices and wearable devices enable person-level tailored treatments. Such behavioural nudges, lifestyle adjustments, monitoring, and alerts will be used to deliver personalised suggestions [24]–[28]–[35]. These technologies are specifically tailored to oversee the effectiveness of recommended interventions and gather secondary data from patients, which will be analysed subsequently to produce more comprehensive information. This information may include connections, interactions, situations, habits, and behaviours that may affect health, prevention, or long-term conditions. These statistics will be used to assess the effectiveness of suggested suggestions (prevention and intervention actions) and to identify new dangers.

To enable an ongoing tracking and evaluation cycle, HHRs are produced by harmonising and integrating primary and secondary information. The information is subsequently saved in the iHELP platform [36]–[38]. The iHELP platform amalgamates investigations into sophisticated AI methodologies with innovative strategies for data modeling, administration, and system interoperability. iHELP provides a crucial clinical-ICT framework that standardises data models and organises to manage heterogeneous datasets, facilitates sharing information in clinical decision-making, and improves quality of life and health awareness. The following diagram illustrates the foregoing:

Fig. 2: AI iHELP Dataset Platform



Source: Authors, 2022

The Fig. 2 consists of the following algorithms:

Algorithm 1: Max Pooling Calculation

INPUT: Image

OUTPUT: Calculate Max Pooling.

1. Max pooling – applied to the output mapping feature (convolutional operations detector line) with a modified random forest

2. Pooling line

3. For stride, the max operation is computed as

4. MaxPooling2D

6. Define vertical line detector

7. Store the weight in the max pooling model.weights_set

8. Apply the data filter: yhat = model.predict (data).

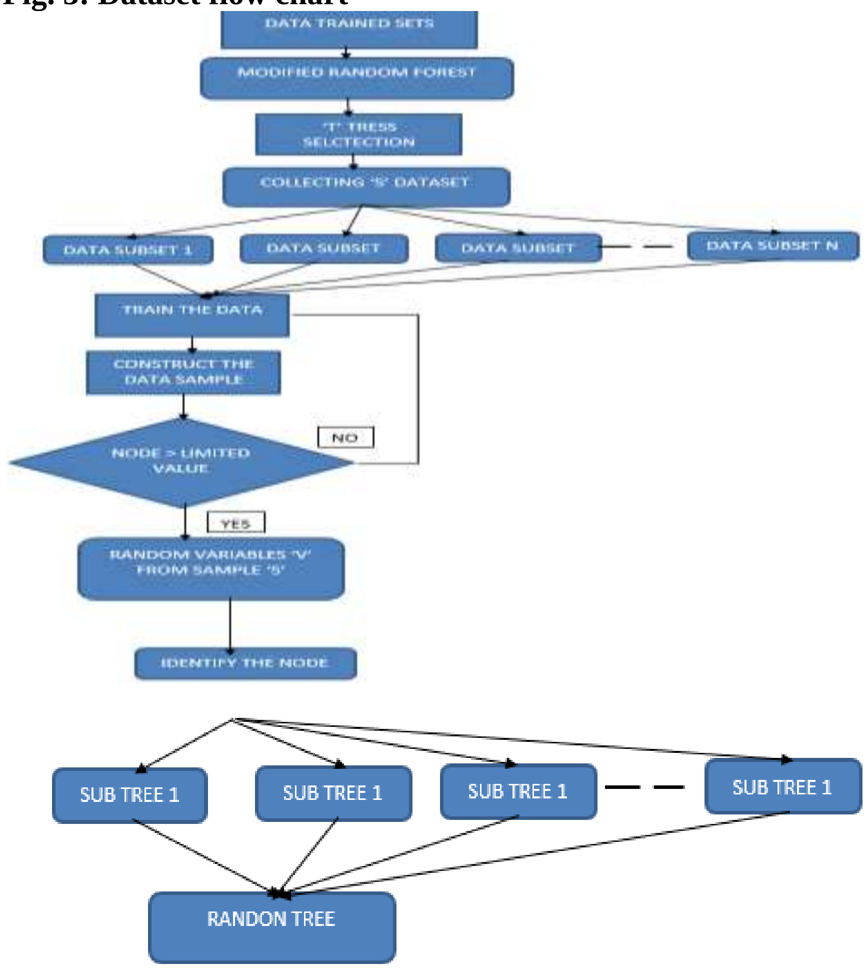
Algorithm 2: Modified Random Forest Algorithm

Input: Datasets
Output: Binary Tree
Initialization

Tree 'T' selected for sub-tree
Data collection
Subset 'S' initialising subset 1 to 'n' tree
Train data
Create 'N'-sized data samples
Stop when node value is low
Choose the random variable 'V' from sample 'S'
Tree splits into 'n' leaf sub-trees based on Node.
Generate random tree
Stop

See the proposed flow chart below:

Fig. 3: Dataset flow chart



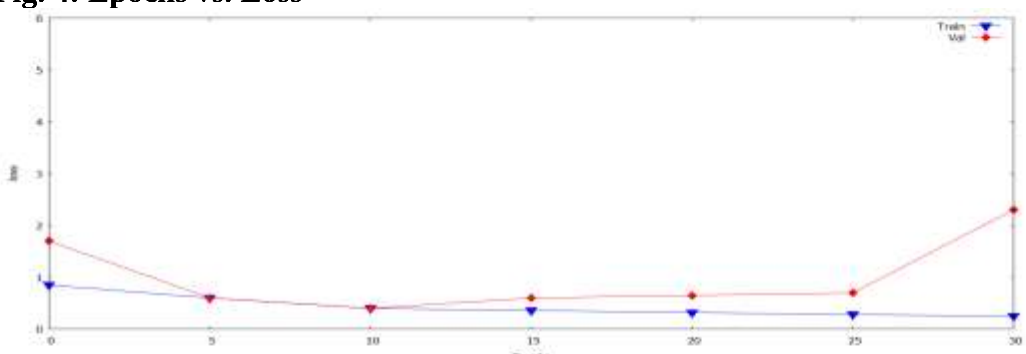
Source: Authors, 2022

Performance Analysis

As data intelligence grows in health care and intelligent appliances, there is an increasing amount of data to be examined utilising big data. An important part of carrying out the process of monitoring patient healthcare is machine learning. Therefore, according to patient-specific measures, the patient typically overcomes the challenge of variance in the more significant dataset number and complexity and efficiently obtaining the data. We provide an intelligent learning framework that is combined with machine learning, based on the healthcare application, to enhance the assessment of patient monitoring using patient care metrics, including data correctness, cost, and time complexity.

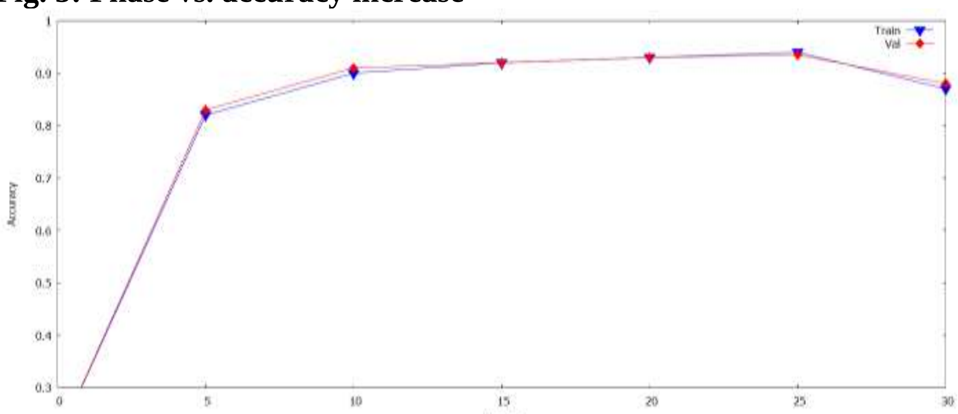
The patient treatment procedure consists of three phases. The phases are pre-treatment, in-treatment, and post-treatment. It also facilitates the detection and monitoring of cancer. Thus, the characteristics linked to breast cancer healthcare data scalability with adaptability are evaluated. By changing the epochs from 0 to 30, Figure 4 computes the loss, using the categorisation model. The saturation of the loss occurs as the recommended value increases across epochs. See the figures 4-7 below:

Fig. 4: Epochs vs. Loss



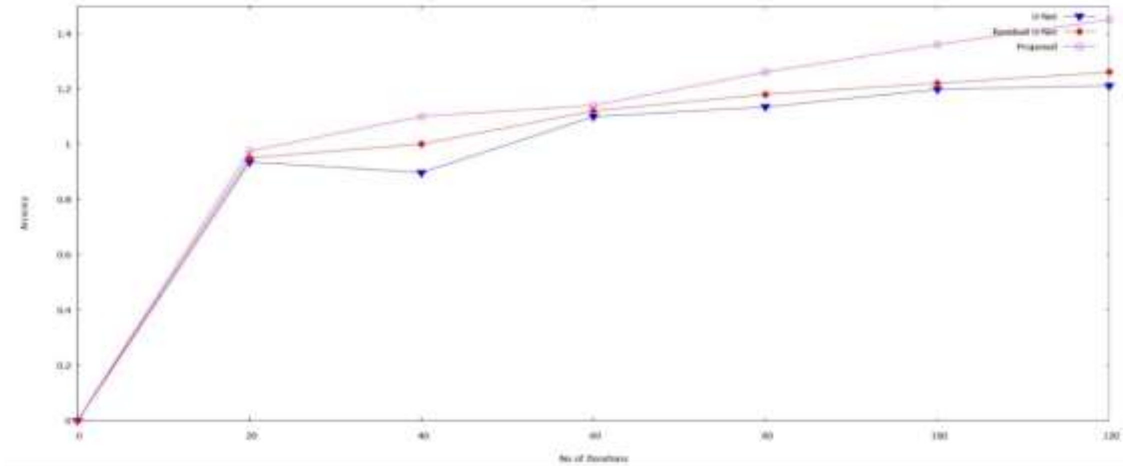
Source: Authors, 2022

Fig. 5: Phase vs. accuracy increase



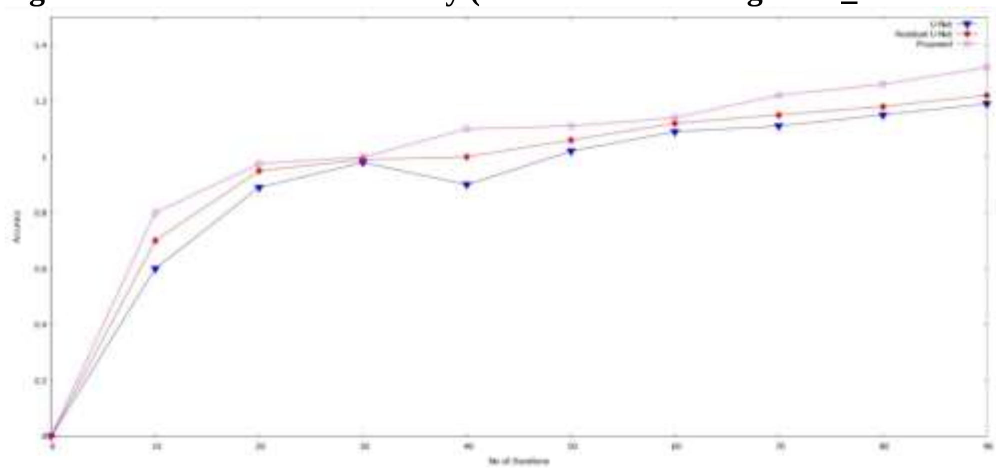
Source: Authors, 2022

Fig. 6: No. of iteration vs. accuracy (Loss Function: focal_tversky)



Source: Authors, 2022

Fig. 7: No of iteration vs accuracy (Loss Function: categorical_crossentropy)



Source: Authors, 2022

Accordingly, as phases increase from 0 to 30, accuracy increases. Figures 4 and 5 depict it. Different loss function models, such as focal_tversky and categorical_cross entropy, are used in Figures 6 and 7. The accuracy is determined by comparing the suggested Res U-Net to the present one and changing iterations. The precision increases with iterations. The loss function depicted in Figure 6 is specific to focal_tversky. Category_cross entropy for the loss function is shown in Figure 7.

Conclusion

In spite of data analytic techniques' prosperity of proof on pancreatic cancer datasets and recent developments within treatment, a great deal of hazards and related situations remain unanalysed, necessitating the necessity for focused suggestions. By providing insights into pancreatic cancer detection, prevention, and treatment involving AI techniques, the iHELP platform has promising potentials to tackle pancreatic cancer. The iHELP innovation seeks to establish a new personalised hospital to collect, combine, and standardise health data from medical records, lifestyle choices, behaviours, and social media interactions. The study has shown that iHELP is a Holistic Health Record (HHR) system of technological innovation in healthcare.

With iHELP, real-time risk prediction, multi-modal causal analysis, and anomaly detection obtain significantly. With AI techniques, iHELP can be used to develop resilient instructional techniques that foster effective and proactive decisions through the method of risk-free forecasts and individualised preventive actions. These are aimed at intervening user-centric cell phones and wearable apps delivering warnings, behavioral nudges, consultations, prescriptions, therapies, screening, etc. The iHELP outcomes can do more than only compile information from many sources. They have obviously opened up possibilities for creating problem-solving AI methods (techniques) that can simulate the unique circumstances of each pancreatic cancer patient and produce accurate predictions that may be employed to develop effective care plans.

Finally, by virtue of integrative functionality, HHRs help validate iHELP outcomes, including quality of life and risk reduction through powerful analytic tools. Therefore, iHELP solutions are bound to help policy-makers establish new screening programmes and guidelines for improving clinical, lifestyle, and behavioural aspects of pancreatic cancer therapies and other related remedies. These include providing choice support and sociological analysis. The proposed iHELP approach and platform can be evaluated further by using data from many cohorts/regions in the EU and beyond to verify data models. And, as it is realised that AI-based analytics get closer and facilitate knowledge exchange and collaboration among physicians, researchers, and policymakers, there is need for full integration of AI techniques into healthcare practices, discourses and researches.

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