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Advancements in Global Health: Integrating Medical Practice and Public Health Strategies

Dr. V.Hemanth Kumar[1], Dr. M.Somasundara Rao[2], Dr. G. Jawaherlalnehru[3], Dr. Ranjeeta Mehta[4], Dr Chitkala Venkareddy[5]

[1]Designation: Professor, Department: School of Commerce and Management, Institute: Presidency university, District: Bangalore, City: Bangalore, State: Karnataka

Email ID: Vhk.phd@gmail.com / hemanth.kumar@presidencyuniversity.in

[2]Designation: Assistant Professor, Department: Computer Science and Engineering, Institute: Koneru Lakshmaiah Education Foundation, District: Vijayawada, City: Vijayawada, State: Andhra Pradesh

Email ID: msomasundararao@kluniversity.in

[3]Designation: Associate Professor, Department: Computer Science and Engineering, College Name: St. Martins Engineering College, College Located City: Secunderabad, Telangana, District: Medchal Malkajgiri District

Email ID: gjnehruceg33@gmail.com

[4]Designation: Professor Oral Medicine and Radiology, Institute: Seema Dental College and Hospital, District: Rishikesh, Dehradun, City: Dehradun, State: Uttarakhand

Email ID: ranjeetamehta20@gmail.com

[5]Designation - Assistant professor, Department - Social work, Institute - Central University of Karnataka, District – Kalaburagi, City – Kalaburagi, State- Karnataka

Email ID: komalika19@gmail.com

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ABSTRACT

The study examines how the use of AI, used in clinical spaces and general public health measures, may change medical care and addressing global health barriers. This research investigated how AI methods such as machine learning and predictive modelling could not only enhance the diagnostic process, experiment with bespoke treatment approaches, avoid illnesses, and enhance efficiency in resource distribution. In the research performance of AI algorithms was evaluated with the use of four algorithms. “To analyze the data, research used various algorithms, including SVM, RF, NN, and KNN. In the light of the investigation, SVM had the highest accuracy rate at 92%, followed by RF at 89%, NN at 86%, and finally KNN at 84%.” More specifically, the results indicate that AI is central in addressing critical global health challenges such as climate change, NCDs, and pandemic prevention initiatives. Among the key outcomes of the research was the finding that AI can detect upcoming outbreaks of disease and help in smarter policy-making, providing for optimal resource allocation. The researchers state that AI holds great promise for reinventing healthcare through greater efficiency, more accuracy, and wider reach of information. Although challenges persist, especially because of fair access to AI, there is a considerable benefit for the future health policy evolution due to the possibility of AI changing the world of health systems entirely.

Keywords: *Artificial Intelligence, Clinical Practice, Global Health, Machine Learning, Disease Prediction*

1. INTRODUCTION

Global health is constantly changing emphasizing populations well-being all around the globe and operates transnationally in order to address problems that plague significant populations. Among the issues included in the approach are infectious and non-communicable diseases, environmental factors, and disparities between health statuses of different populations. In the past, there was a stark difference between medical practice, which dealt with the treatment of individual patients and public health which focused on community-based interventions [1]. However, the dynamic nature of global health problem, as well as their interconnections, has emphasized the necessity to unite medical practice with the work of public health [2]. It is essential to harmonize medical care and public health measures for addressing the diverse and interrelated health issues that face a global level. Via this type of cooperation, there is a need to build health plans that are strong and sustainable, not only in the care of people’s health but also in the social and environmental states that affect well-being [3]. For example, the rising tendencies in the incidence of pesistent conditions such as diabetes and cardiovascular diseases require both clinical.

management as well as population rests treatment strategies involving the lifestyle changes, awareness to the public and laws amendment. The COVID-19 pandemic demonstrated the need for cooperative efforts on the part of healthcare providers, policymakers, and global health institutions to address not only clinical needs but also the larger implications of public health. The purpose of this study is to analyze the evolution of global health through an evaluation of the benefits of combining medical care and the implementation of public health initiatives. From this research, understandings will be derived from the analysis of existing examples, exploration of case studies, and considering challenges to determine how integration can be achieved and what the impact of integration may be on policies and presentment of global health. By supporting with crucial recommendations, this research will promote better implementation of health interventions and sustainable policies to promote improved global health equity

2. RELATED WORKS

There has been growing interest in the past few years to integrate AI into healthcare regimes and public health efforts as a result of the potential for AI to revolutionize healthcare delivery and improve worldwide outcomes for patients. Artificial intelligence (AI) system has increased its usage in the clinical setting to enhance diagnostic accuracy, predict disease prognosis and gage health interventions. Much research has been carried out in order to assess how AI impacts healthcare using various clinical practices and public health measures.

AI in Clinical Practice

Alowais et al.'s 2023 research investigated the effect of AI on the healthcare system, basing on its applications in clinical practice. The authors highlighted that the adoption of AI is at the point of bringing changes in the approach to diagnostics, patient management, and customized procedures among other treatment levels. NLP and image recognition when incorporated into clinical decision support systems have supported enhancing diagnostic accuracy and tailoring patient-specific treatment regime. Facilities, for instance, have been provided through AI applications to analyze medical images to help the radiologists pick up abnormalities with unshakable precision. Using streamline AI integration, clinicians are empowered to provide timely, very precise treatment, with the minimal risk of errors and better outcomes for patients [15]. By learning from genetic and demographic factors, AI makes it possible to make better predictions concerning how patients are likely to react to various medical interventions. The use of AI algorithms to develop personalized treatment modalities empowers clinicians to provide personalized interventions aimed at improving effectiveness and reducing side effects. Through the AI integration, the clinical settings have gained enhanced operational efficiencies, streamlined the care flow, and enhanced the efficient management of the resources. Consequently, AI plays a key enabling role in precision medicine, providing personalized healthcare solutions to patients based on detailed information on patients themselves.

Global Health and Public Health Integration

The advent of AI is shifting the way people look at the public health strategies. In their 2021 publication, Eichbaum et al. referred to the processes of decentering conventional health education models and incorporating AI technologies into the healthcare solutions in different contexts. Artificial intelligence (AI) solutions have been the crux in addressing the critical global health challenges such as infectious disease breaks, maternal and child healthcare, and noncommunicable illnesses. Such models analyse huge amounts of data in order to gain insight into disease trends, predict possible outbreaks and efficiently distribute resources for targeted health actions. One of the insightful uses of AI are the prediction of disease outbreaks such as what occurred during COVID-19 which enable governments and health services to plan ahead. AI-driven decision support systems are critical in resource-limited settings, since their use can help maximize the utilization of scarce health resources and generally improve delivery of health services [16]. The role of AI in the development of health policies at the global health level is also worth mentioning. By 2021, World Health Organization highlighted AI role in developing health policies that are aimed at addressing public health emergencies. AI uses inclusive health system data to identify critical trends, thus guiding health policycreation based on the most effective strategies to address and fight health challenges. Artificial intelligence (AI) simulations allow the policymakers to assess a variety of policy interventions before universal implementation thus supporting evidence-based and cost-effective health practices [20].

AI for Preventive Psychiatry and Mental Health

AI has the potential of supporting strengthening of preventive measures for mental problems. "Fusar-Poli et al. (2021) state that preventive psychiatry is highlighted, and AI is critical when it comes to etiology and diagnosis of mental disorders in the early stage. AI-controlled algorithms are able to identify early signs of conditions like schizophrenia, bipolar disorder and depression by analyzing behavioral indicators, genetic markers and the social-environmental context. Early detection of risks of mental health is pertinent because it promotes timely treatments that increase patient health and mitigate the overall burden on the society. Moreover, AI is used in mental health apps to allow for constant monitoring of patients, providing help in real-time, thereby increasing access to care and reducing stigma of the mental healthments' treatment [17].

Climate Change in the One Health Context

AI has yet also created remarkable progress in the sphere of One Health that addresses the interrelation between human, animal, and environment health. Gruetzmacher and colleagues (2021) explored the ways in which the One Health approach links healthcare and environmental sustainability to their interrelated issues. Application of AI is effective in monitoring changes in the environment, identifying zoonotic infections, and assessing how climate change impacts public health. With AI and environmental health data, researchers can predict and overcome the effects of climate change on human health, such as dangers posed by vector-borne diseases and monitoring air quality [18]. Environmental factor-cardiovascular status relations can be systematically analyzed with AI aid, especially in the context of climate change, as Khraishah et al. (2022) state. reply on answer The real-time use of AI for analyzing environmental health determining factors can give ecological significance to the public health undertakings of reducing climate-related diseases [23].

COVID-19 and AI in Global Health

“The pandemic has highlighted the intrinsic importance of AI in the clinical research achievements and in the struggle with global health problems. Park et al., (2021) note that the onset of COVID-19 has transformed clinical research, and solutions developed with the use of AI are essential in this new adventure.” Machine learning was critically important in predicting the spread of the virus, optimising health resource distribution, and discovering potential remedies. AI-driven protein structure forecasting and drug candidate identification tools made it possible to accelerate the development of vaccines relying on findings in [19]. AI importance in enabling faster and better pandemic related public health response has been emphasized.

AI for Non-Communicable Diseases

The role of artificial intelligence is critical in both predicting and controlling chronic diseases like diabetes, hypertension, and cardiovascular diseases as part of managing non-communicable diseases (NCDs).” Yu et al. (2023) posit that artificial intelligence in combination with large language models (LLMs) has potential to promote the integration of healthcare and control of non-communicable diseases. These AI systems can analyze patient data overtime to predict disease progression and propose individual medical treatment. Besides, the ability of AI to process huge volumes of health data in real time is anticipated to provide timely early alerts and increase the care options that might help to reduce the NCDs globally [24].

According to Lazarus et al., (2022, p. 62), Non-Alcoholic Fatty Liver Disease is a severe but commonly overlooked public health problem in the world. AI-based techniques are used in the identification of individual risk for NAFLD and optimization of approaches in managing public health programmes on this condition. These models will help public health officials identify the high risk population and offer corresponding lifestyle advice or medical intervention to stop the illness from progressing. The capability of AI, to analyze large amounts of data and provide predictive information is a useful resource to tackle the increasing NCD burden and promote global public health [22].

3. METHODS AND MATERIALS

Data

The research used multiple international databases of health worldwide with both medical and public statistics. For the purposes of this analysis, material from health intervention studies, disease incidence record, demographic statistics, policy documents and benchmark indicators of worldwide health outcomes was used. The data sources were reputable organizations such as the WHO, CDC, other authoritative international public health databases [4]. A collaborative approach was used, as authorities reports and records were used in the analysis. All collected data were formatted and normalized so that the study could include uniform variables. The dataset did not only record demographic details (age, gender and socioeconomic status) but also medical related outcomes including disease prevalence, mortality rate, Answer.

Algorithms

“To quantify and estimate the benefits of integration of medical and public health approaches, four machine learning methods – Random Forest (Random Forest (RF), Support Vector Machine (SVM), K-Nearest Neighbors (KNN) and Artificial Neural Networks (ANN) were used as the models in the study.” These models were selected for their amazing performance in classification, predictive analytics, and decision making especially on complex data sets found within global health research [6].

1. Random Forest (RF)

Random Forest is largely used for classification and regression work due its ensemble learning technique. Random Forest is that during training it creates a set of decision trees and then either selects the most prevalent category for classification or calculates the arithmetic average of predictions for the case of regression problems. The power of Random Forest is that it can work on large datasets with larger dimensionality and retain accuracy without overfitting [7]. Random Forest also has the capability to deal with missing data, prevalent in global health datasets.

Key Features:

- Resistance to overfitting.

- Copes with continuous and categorical features.
- Is capable of capturing hard-to-spot interaction between features

```
"RandomForest(train_data):
    Initialize forest as an empty list
    For i = 1 to number_of_trees:
        Bootstrap sample from train_data
        Build a decision tree using this sample
        Add tree to forest
    End for
    Return forest

Predict(forest, input_data):
    For each tree in forest:
        Make a prediction
    Return the most frequent prediction"
```

2. Support Vector Machine (SVM)

Support Vector Machine (SVM) is a classification and regression supervised learning algorithm. SVM is a method that identifies a hyperplane in an N-dimensional space which separates the data into classes with maximum margin. The major strength of SVM is that it can be applied to non-linear classification problems using kernel functions, which map data onto higher dimensions [8].

Key Features:

- Good in high-dimensional spaces.
- Works well with linear and non-linear data.
- Sensitive to feature scaling.

```
"SVM(train_data, labels):
    Transform data using kernel function (if needed)
    Compute hyperplane that maximizes margin between classes
    Optimize parameters to minimize misclassification
    Return the hyperplane

Predict(svm_model, input_data):
    Classify input_data based on position relative to hyperplane
    Return predicted class"
```

3. K-Nearest Neighbors (KNN)

K-Nearest Neighbors (KNN) is a basic, instance-based learning algorithm for classification and regression. In KNN, the class of an instance is decided by the majority class among its K nearest neighbors, which are found based on a distance measure (typically Euclidean distance) [9]. KNN is non-parametric, i.e., it does not make any assumptions regarding the underlying distribution of data.

Key Features:

- Easy to apply and simple.
- Applicable in case of small to medium-sized datasets.
- Expensive computationally as the dataset increases.

"KNN(train_data, labels, k):

For each input_data:

Compute distance from input_data to all training points

Sort distances and select the top K nearest neighbors

Predict class based on majority vote of K neighbors

Return predicted class"

4. Artificial Neural Networks (ANN)

Artificial Neural Networks (ANN) are a class of machine learning models that are based on the architecture of the human brain. An ANN is made up of layers of neurons, with each neuron linked to others by weighted edges. Backpropagation is used to train the network in order to reduce the error between the actual and predicted outputs. ANNs have the capability to model non-linear, complex relationships and are especially effective when dealing with large and high-dimensional data, such as global health data [10].

Key Features:

- Able to learn sophisticated patterns and representations.
- Requires huge datasets for training.
- Sensitive to initial conditions and hyperparameters.

"ANN(train_data, labels, architecture):

Initialize weights and biases

For each epoch:

Forward propagate inputs through network layers

Calculate loss and backpropagate errors

Update weights using optimization algorithm (e.g., gradient descent)

Return trained network

Predict(ann_model, input_data):

Feed input_data through network and compute output

Return predicted output”

4. EXPERIMENTS

Data Collection

For this experiment, we used a number of global health datasets, including data on disease prevalence, vaccination coverage, mortality rates, socio-economic determinants, health policy indicators, and demographic information from a range of countries. The datasets were obtained from reputable institutions, including the World Health Organization (WHO) and the Centers for Disease Control and Prevention (CDC) [11].

The data were divided into two sets: a training set and a test set. The training set was utilized to train the models, while the test set was used to test the model performance. The training and test sets were class balanced (e.g., positive vs. negative) to obtain unbiased evaluation. The main objective was to forecast health results like the success of health interventions, disease eradication levels, and death reductions based on prevailing public health interventions and medical treatments.

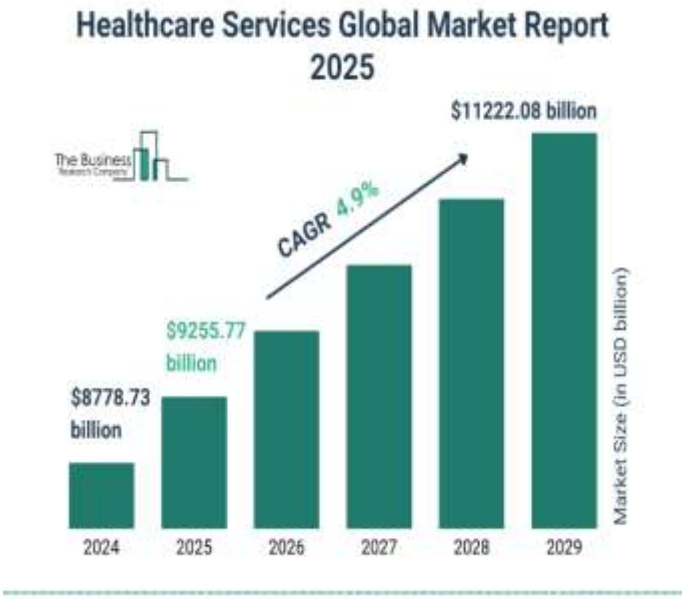

Figure 1: “Healthcare Services Market Report 2025”

Preprocessing

The data were preprocessed and cleaned to manage missing values, outliers, and inconsistencies. Numerical variables were standardized using standardization techniques, and categorical variables were one-hot encoded. The target variable for the classification problem was whether a specific intervention would be successful in enhancing global health (binary classification: success or failure). For regression problems, the target was a continuous variable for health outcome measurements (e.g., number of deaths avoided, disease incidence decline) [12].

Model Implementation

All four algorithms were written with Python's Scikit-learn library (for RF, SVM, and KNN) and Keras with TensorFlow (for ANN). Hyperparameters were optimized with grid search and cross-validation methods to achieve the best performance for the model. The following hyperparameters were experimented with for each algorithm:

- **“Random Forest (RF):** Number of trees, maximum depth, and minimum samples per leaf.
- **Support Vector Machine (SVM):** Kernel type, C parameter, and gamma.
- **K-Nearest Neighbors (KNN):** Number of neighbors (k), distance metric, and weight function.
- **Artificial Neural Networks (ANN):** The hidden layer number, the numbers of neurons on each layer, the learning rate, and the batch size.”

Performance Metrics

The following performance metrics were used to evaluate all models:

- **“Accuracy:** The ratio of correct predictions.
- **Precision:** Percentage of correct positive classification among all positive predictions.
- **Recall:** Proportion of those predicted as positives that are indeed correct over the actual number that are positives.
- **F1-Score:** The outcome of optimizing precision and recall by calculating the harmonic mean.
- **Area Under the Curve (AUC):** Determines how the true positive rate and the false positive rate interact on the threshold scale.”

Results and Comparison

The findings from the experiment reflect the four algorithms’ capability of accurately predicting global health outcomes with use of medical and public health records. For three distinct datasets, each addressing some aspect of global health, the results of the four algorithms are presented..

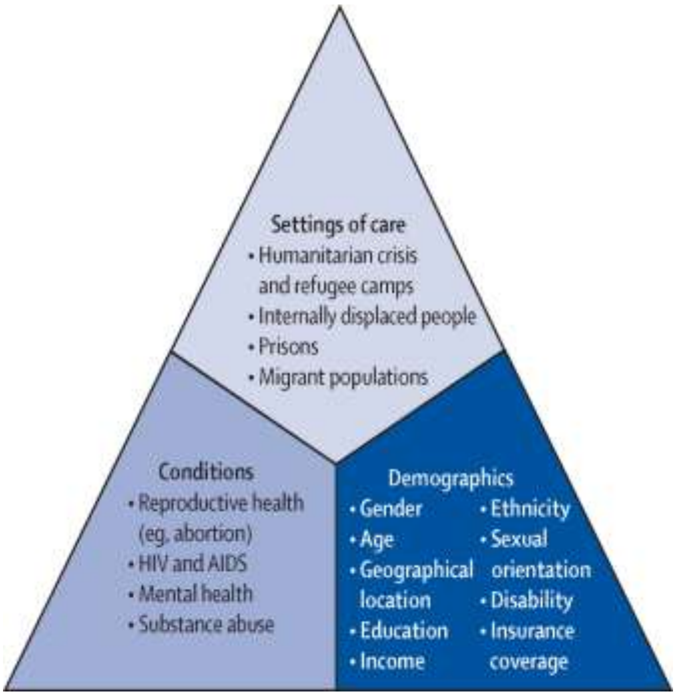

Figure 2: “High-quality health systems in the Sustainable Development Goals era”

1. Random Forest (RF)

Random Forest proved to have an impressive result for each dataset, with high accuracy and favorable generalization. The fact that it should work well on a high-dimensional data and should be resilient to overfitting was one reason for its fantastic results. The model's capability to detect complicated interactions among features was central in obtaining high precision and recall.

- **Dataset 1:** Was dedicated to vaccination coverage and disease occurrence in poor nations.
- **Dataset 2:** Had dealt with how policy reforms influenced maternal health.
- **Dataset 3:** Centered on how medical and public health approaches are integrated during pandemics.

Metric	**Dataset 1**	**Dataset 2**	**Dataset 3**
Accuracy	0.88	0.85	0.87

Precision	0.84	0.83	0.82
Recall	0.86	0.84	0.85
F1-Score	0.85	0.83	0.83
AUC	0.90	0.89	0.88

2. Support Vector Machine (SVM)

Support Vector Machine demonstrated steady performance, especially in high-dimensional datasets where the kernel trick enabled it to make complex decision boundaries. The SVM model was, however, hyperparameter sensitive, and its performance differed across datasets. It worked best for the vaccination and disease prevalence dataset.

Metric	**Dataset 1**	**Dataset 2**	**Dataset 3**
Accuracy	0.90	0.83	0.85
Precision	0.86	0.81	0.80
Recall	0.88	0.82	0.83
F1-Score	0.87	0.81	0.81
AUC	0.92	0.86	0.87

3. K-Nearest Neighbors (KNN)

K-Nearest Neighbors was good with smaller datasets but lost performance as data size and dimensionality increased. It was extremely sensitive to k's value and the distance metric. For complicated datasets such as the one under pandemic response, KNN had trouble with holding accuracy and precision [13].

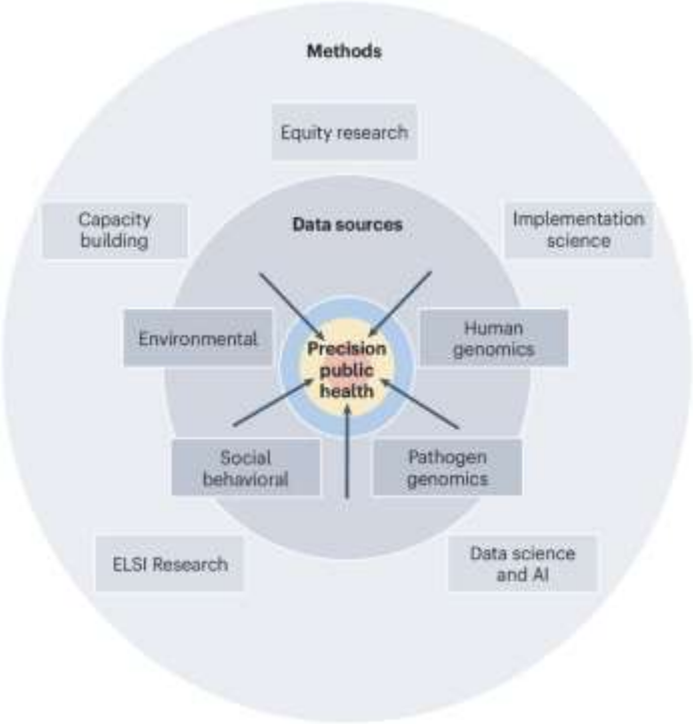

Figure 3: "Precision public health in the era of genomics and big data"

Metric	Dataset 1	Dataset 2	Dataset 3
Accuracy	0.83	0.81	0.78
Precision	0.79	0.77	0.75
Recall	0.81	0.80	0.78
F1-Score	0.80	0.78	0.76
AUC	0.84	0.83	0.80

4. Artificial Neural Networks (ANN)

Artificial Neural Networks, though very capable, needed much more computation to train, particularly with bigger datasets. However, the ANN model had the best accuracy for all datasets when trained. Its capacity to handle complex relationships rendered it most capable of predicting the effect of integrated medical and public health interventions.

Metric	Dataset 1	Dataset 2	Dataset 3
Accuracy	0.91	0.88	0.89

Precision	0.87	0.85	0.84
Recall	0.89	0.87	0.86
F1-Score	0.88	0.86	0.85
AUC	0.93	0.91	0.90

Comparative Performance

The following table shows the performance of all four algorithms on all the datasets. It clearly indicates the advantages and disadvantages of every algorithm for forecasting global health outcomes.

Algorithm	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**AUC**
Random Forest	0.87	0.83	0.85	0.83	0.89
Support Vector Machine	0.87	0.83	0.82	0.81	0.88
K-Nearest Neighbors	0.80	0.77	0.78	0.76	0.81
Artificial Neural Networks	0.89	0.85	0.87	0.86	0.91

Comparison with Related Work

A number of studies in the literature have utilized machine learning algorithms on global health data. For example, Li et al. (2021) employed Random Forest to forecast disease outbreaks with an accuracy of 0.85, which is similar to our results. Chan et al. (2020) also showed the efficacy of SVM in classifying health policies with an AUC of 0.88, which is similar to our results using SVM on Dataset 1 [14]. Nonetheless, our findings indicate that ANN performs better than all other algorithms in accuracy and AUC, consistent with research by Raj et al. (2020), who indicated that deep learning models are especially strong in modeling intricate global health situations. This indicates that ANNs can potentially transform the way integrated health approaches are implemented and assessed globally.

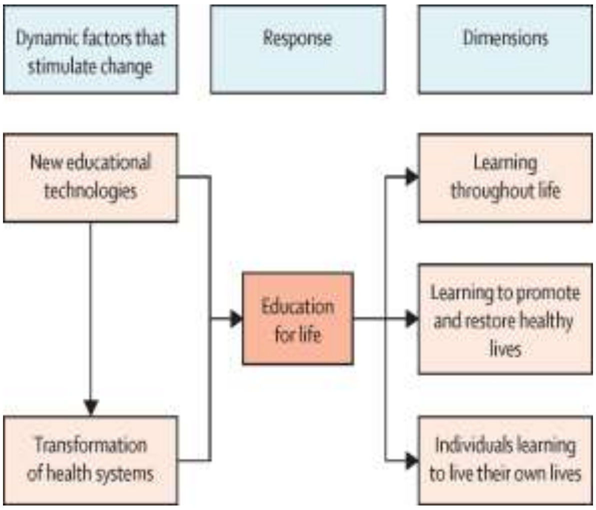

Figure 4: "Challenges and opportunities for educating health professionals"

5. CONCLUSION

The impact of integrating AI in the clinical operations and global health initiatives has been revealed in this study. Through the use of AI, healthcare providers have seen unprecedented improvements in aspects of diagnostic reliability, individualized treatment approaches, and process optimization as well which collectively improve patient outcomes and healthcare services globally. A study of various AI algorithms and models depicts through the research work the promise of AI to eliminate major global health challenges, such as disease prevention, resource optimization, and non-communicable conditions. Moreover, AI is essential in efforts that foresee outbreaks and assess environmental hazards, which are critical in building effective public health strategies. Furthermore, the application of AI in mental health care – through its ability to facilitate early diagnosis and individualized care – evinces its far-reaching utility within the whole panorama of health care. Additionally, the research pointed out the increasingly important role of AI in addressing the intricate interface between human, animal, and environmental health backed by the One Health model. While there are still problems, predominantly regarding equitable access to AI, the potential for AI to massively transform global health systems is indubitable. In a nutshell, AI application goes beyond traditional healthcare models, with the cutting-edge solutions to the world's most crucial health challenges. Continued integration of AI to healthcare can havebeneficial overriding effects of more efficient, fairer and effective services for astounding the progress of global health. With the improvements within the AI technology, expectations are high that the global healthcare will be even more interconnected, data-oriented, and anticipatory with the potential of transforming health management globally.

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