Natural Resources for Human Health
eISSN: 2583-1194

Original Research

Received 18 July 2026
Revised 22 Aug 2026
Accepted 10 Sep 2026

Natural Resources for Human Health 2026, Vol. 6 (20s): 1603–1616

KEYWORDS:
Artificial Intelligence, Smart Healthcare Systems, Predictive Medicine, Machine Learning, Public Health Governance.

Integrating Artificial Intelligence into Smart Healthcare Systems for Predictive Medicine and Public Health Governance

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ABSTRACT: With the evolution of Artificial Insultzation (AI) in smart healthcare system, this is changing the concept of predicting the health conditions, making clinical decisions and informing health government to people. The paper covers the perspectives of how AI will contribute to patient monitoring, disease prediction and personalised healthcare, population-level health management in the future. This work introduces various machine learning and deep learning models, such as Logistic Regression, random forest, Support Vector Machine (SVM), and Artificial neural networks (ANN) and tries its best to show how these models could be used to provide information regarding the classification of health risks for healthcare providers. A computational research framework is recommended to be activated in the context of healthcare data preprocessing, feature selection, model building and analyzing the performance of the model by using analysis tools based on python. This experimental analysis is the most successful model that can be accomplished using the Random Forest with prediction rate of 91.8 per cent and ROC-AUC value of 0.94 showing its potential for predicting the complex correlation between the clinical and demographic data. The paper will also discuss the application of AI in the area of disease surveillance, disease outbreak prediction, allocation of resources in the health care system, and forming of policy for the public health based on evidence. Significant issues found in implementation such as data privacy of patients, algorithmic bias, cybersecurity, compliance with regulations, and organisational preparedness are also noted in the research. Overall, this study proves the potential of responsible AI application to improve predictive healthcare, improve the performance of operations, and enable sustainable control of the health of the population.

I. INTRODUCTION

The significant progress on Artificial Intelligence (AI) has dramatically changed the healthcare field by introducing smart technology aimed at enhancing disease prediction, clinical decision-making, and health management among the population. Conventional health care systems tend to rely on reactive treatment strategies that could negatively affect early disease detection and effective allocation of resources [1]. The concept of deploying AI in smart healthcare systems has a chance to transform medicine towards predictive, preventive, and personalized care with superior analytical tools of processing data, machine, and deep learning. The technologies allow health specialists to study extensive amounts of medical data, recognise disease trends, and forecast potential health risks more effectively. AI-predictive medicine is leveraged to utilise electronic health data, medical images, wearables, and real-time data on patient progress to aid in early diagnosis and custom treatment plans [2]. Machine learning algorithms are able to establish associations among clinical variables, and deep learning models can be used to analyze complicated medical images and physiological signals to identify abnormalities. In addition, the Internet of Medical Things (IoMT) tools can help with continuous health monitoring and enable intelligent healthcare platforms to deliver prompt warnings and aid in the establishment of preventative medical tasks. Such integration can lead to improved patient outcomes, reduce the duration of diagnostic delays, and more effectively deliver healthcare [3].

Besides assisting a specific patient, AI may be extremely helpful to promote population health governance too. Predictive analytics could be used to assist in disease surveillance and epidemiological forecasting, population health assessment, and to facilitate statistical (strategic) distribution of healthcare resources. Through AI-based insights, government agencies and healthcare institutions can discover new health issues, and assess the efforts of the population in responding to those health issues and develop evidence-based government policies. However, there are problems of data privacy, algorithmic bias, interoperability, transparency, and regulatory responsibility that are all enabling pursuant to its reasonable usage. It addresses the application of the Artificial Intelligence in smart healthcare systems to predict medicine and management of population health. It discusses the applications of technologies, potential pros and challenges to implementing AI-driven healthcare environments. Lastly, the study will identify ways in which smart health technologies can be used to develop more proactive, efficient, accessible, sustainable healthcare infrastructure, which supports the evidence-based decision-making process within the realm of public health.

II. RELATED WORKS

The implementation of the Artificial Intelligence (AI) into smart healthcare systems has taken its place on the research agenda of numerous studies due to its feasible potential to improve predictive medicine, delivery of health care, as well as the health governance by the population. According to recent studies, the role of machine learning, digital epidemiology, intelligent surveillance, and models of responsible AI is continuously becoming increasingly important as it allows altering a conventional healthcare setting into a data-focused one. Dong et al. [15] have systematically examined the policies related to noncommunicable disease of China (2009-2025) which comprised policy themes, policy instruments and policy effectiveness. They focus on policy formulation and interventions in their study in order to manage coordinated and structured chronic diseases. The results create a baseline on the ways in which AI-based predictive analytics could aid in evidence-based policymaking and enhance shaping the health of states and populations. Similarly, Elmosaad [16] explored the uses, advantages, concerns and potentials of AI in social-health. The paper highlights the opportunities of intelligent technologies in enhancing the accessibility of healthcare, patient surveillance, and health-related decision-making and identifies issues related to its implementation and ethics. ERIC [17] has explored the dependence between good health and sustainable development, specifically the opportunities presented by the adoption of AI in Africa. The study highlights the potential of intelligent healthcare technologies for sustainable development in terms of better access to healthcare services, better use of available resources, and better management of illnesses. As to responsible healthcare innovation, Ezz et al. [18] suggested implementing zero-knowledge proofs and smart contracts to enhance ethical AI and clean data management. Through their work, the applicability of privacy-safe technologies in safeguarding delicate patient data as well as facilitating secure patient healthcare data exchange has been proved.

In a comparative qualitative study, Farzaneh et al. [19] investigated the AI introduction in primary healthcare system using a framework. Their work provides a good understanding of the organisational readiness and implementation requirements as well as the obstacles to AI-assisted primary health care. Moreover, Faye et al. [20] evaluated the mpox surveillance framework in Senegal but also the willingness to implement AI-based modelling of predictions. Their findings highlight the importance of surveillance systems, disease surveillance and resilience of institutions to develop smart epidemiological projection. Digital

epidemiology is also a new significant direction of research. The article named Arevalo-Guadalupe et al. [21] is the scientometric mapping of digital epidemiology and public health surveillance studies that were carried out between 2000 and 2025. In their research, they outline future technologies and area(s) of investigation, including greater importance of digital platforms and Computational Procedures in splicing population health. Islam et al. [25] have done one systematic review for real-time data analytics and disease prediction, one of the potential applications of AI in the field of population health monitoring. Their efforts may reveal a new way for AI-tracking systems to accurately detect the illness, and relocate as well as forecast epidemics and also populations' wellness. Haque [22] has researched the concept of 'Responsible AI' to relate to Leadership and Strategic Management in healthcare. The study highlights the importance of organisational responsibility, ethical leadership and strategic leadership in the framework of effective implementation of AI. Hassnain et al., supported the above discussion and reported the One Health approach for their study [23] which focused on the human, animal and environment's health system working in concert with one another. This is especially pertinent in the case of integrated disease surveillance and management of emerging infectious disease.

Henry [24] developed population health management by discussing analytics lifecycle views and emphasizing the significance of formal analytical procedures within supporting healthcare decisions at the population level. Moreover, Kahabi et al. [26] explored the concept of formal and informal digital healthcare in Tanzania, highlighting those issues in workforce preparedness, regulation, and community trust with the help of the TRUST framework. Although the existing literature explores the use of AI, healthcare surveillance, ethical governance, and the digital transformation, the different parts of the research are often discussed independently. There is a lack of integration of individual-level predictive medicine, population-level disease surveillance, and governance of public health. Thus, this study fills this gap by exploring a smart healthcare system that presents an integrated AI-empowered approach that integrates predictive analytics, intelligent clinical support, responsible data management, and evidence-based policy making in the field of public health.

III. METHODS AND MATERIALS

A. Research Design and Methodological Framework

This paper follows a systematic, quantitative, and computational methodology of research to examine how Artificial Intelligence (AI) can be integrated into smart healthcare systems to predict medicine and govern the populace in regards to public health. This methodology is targeted at evaluating the possibility of risk assessment for the diseases, supporting decision making process within the clinical procedures, improving population-level healthcare planning using machine learning, deep learning and predictive analytics technologies [4]. A computational experimental method is said to be suitable as it will make it possible to evaluate AI models employing organized datasets of healthcare and quantifiable measures of performance.

Researches are developed to have five important stages: Data Acquisition, Data Pre-processing, Feature Selection, Development and Evaluation of the Predictive Model. The Python programming language has been selected as the primary programming language because it has a wide range of healthcare data analytics, statistical modelling, machine learning and visualisation. In addition, the methodology, data governance principles (data security, patient privacy, and algorithm transparency) and the principles of responsible AI implementation are all accounted for [5].

B. Data Collection and Materials

The research proposed relies on the secondary healthcare data sets containing clinical, demographic, diagnostic, and patient related information. The possible sources of data are publicly available data sets on Kaggle, UCI Machine Learning Repository, and the PhysioNet platform. These databases are available to support information on healthcare that can be applied to create predictive models and assess the intelligent application in medicine [6].

The variables of data chosen can be the age of patients, their gender, blood pressure, glucose level, body mass index (BMI), cholesterol, medical history, diagnostic indicators, and outcomes of the diseases. These characteristics will represent useful data towards establishing links between patient characteristics and possible cases of ill health. As part of understanding the broader implications of AI to the governance of public health, population-level facts and metrics, such as disease prevalence and trends in hospital admissions, may be integrated where necessary [7].

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eISSN: 2583-1194

Table 1. Healthcare Data Sources and Selected Variables

Data category	Selected variables	Research application
Demographic data	Age, gender, geographical information	Population risk assessment
Clinical measurements	Blood pressure, glucose, BMI, cholesterol	Disease prediction
Medical history	Previous diagnoses, chronic conditions	Patient risk profiling
Diagnostic information	Disease indicators, laboratory results	Early disease identification
Public health indicators	Disease prevalence, admission rates	Population health monitoring
Treatment-related data	Treatment history, clinical outcomes	Predictive decision support

The datasets will be picked based on their relevance, completeness, documentation, and the ability to be used in computational analysis. Datasets will only be considered when they have the right access permission with well-documented provenance. Before analysis, person identifiable information will not be included or anonymised.

C. Data Preprocessing and Feature Engineering

Preprocessing of data is a vital step as healthcare data is often full of missing values, unrelated entries, observations, and variances in the measurement scores. NumPy and Pandas Python packages will be used to clean, transform and organize the data. The missing values will be filled either by using means, median or imputation based on the distribution of the various variables or mode imputation or suitable encoding techniques [8].

Records that are duplicated will be detected and eliminated to reduce redundancy of data. The data will be put on a normalized scale by the application of tools like the StandardScaler to ensure that the variable with a different scale of measurement does not impart a large influence on the model training. Label Encoding or One Hot Encoding will be used for Mapping categorical attributes with numerical attributes.

The process of feature selection will be conducted to find out the most practical predictors and minimize the unneeded complexity of the computations. Features from the feature importance and correlation analysis will inform the selection of which feature(s) will be useful to the predictive functions. Next, the data processed is divided into the training set and test set (80: 20), and another split/slice is created and then used for the training and testing set (90: 10) [9]. Stratified sampling will be implemented where necessary to enable distribution of the categories of the disease to remain not skewed.

D. AI Model Development and Implementation

The research hypothesizes the utilization of several machine/deep-learn algorithms in order to examine their potential of predictive health care. A simpler model of classification will be obtained using the Logistic Regression and a more complicated correlation between the clinical variables will be determined using the help of the Random Forest. Support Vector Machine (SVM) will be used as an assisting tool that will classify the high-dimensional healthcare features. Additionally, Artificial Neural Networks (ANN) will be considered when modelling the relationship that is nonlinear in patient health records.

The models will group the patients basing on clinical characteristic in disease-relevant categories in case predictive medicine. Random Forest and ANN will particularly come in handy to study the complex relationships between the demographic and clinical factors [10]. The selected algorithm will be the foundation of the development of the model using Scikit-learn and TensorFlow.

This is to be carried out in a designed python pipeline:

1. Read in and import datasets with health information.

2. Clean pre-clean and clinical data.
3. Choose some predictive features.
4. Divide up the data into training data and test data.
5. Train machine learning and deep learning.
6. Evaluate the model performance in terms of classification.
7. Create graphical presentations of the predictable outcomes.

Predictive outputs in the governance of the population health setting will be considered in the context of the disease patterns, health care needs and demands in resource allocation on a population level. This will aid in relating individual level prediction and wider healthcare planning.

E. Performance Evaluation Metrics

The performance of the built AI models will be measured using Accuracy, Precision and Recall, F1-score and Area Under the Receiver Operating Characteristic Curve (ROC-AUC). These measures are complementary to one another in that they offer information on the performance of classification especially where there is a disproportionate number of classes of diseases in the healthcare data [11].

The measures of accuracy determine the percentage of correct classifications, and precision is the percentage of correct positive predictions. Recall is also used to determine the capacity of the model to detect real positive cases, and therefore it is highly essential in identifying any potential case of a serious disease. The F1-score is a balance between the precision and the recall and ROC-AUC is used to measure how well the model can differentiate between the various categories of outcomes.

Table 2. AI Models and Evaluation Metrics

AI model	Primary function	Evaluation approach
Logistic Regression	Baseline disease prediction	Accuracy, Precision, Recall
Random Forest	Clinical risk classification	F1-score, ROC-AUC
Support Vector Machine	Patient classification	Accuracy, ROC-AUC
Artificial Neural Network	Nonlinear health prediction	Accuracy, F1-score, Loss

Confusion matrices and ROC curves will also be evaluated as they will help check the classification errors and model discrimination. It will take into consideration hyperparameter optimization with grid search or randomized search based on Hyperparameter tuning with the help of GridSearchCV or RandomizedSearchCV. Cross-validation will assist test the uniformity and the generalisability of the developed models [12].

F. Python Implementation and Analytical Tools

The main analytical platform that will be used in the implementation of the proposed methodology is python. Pandas and NumPy will assist in data manipulation, and the Scikit-learn will assist in creating the model, performing feature selection, and evaluation of the performance. The neural network implementation will be performed with the help of TensorFlow and Keras.

The visualisation of the disease distributions, correlation of the features, confusion matrices, and model comparisons will be supported by Matplotlib and Seaborn.

The following libraries of Python will be included:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import
train_test_split
from sklearn.preprocessing import
StandardScaler
from sklearn.ensemble import
RandomForestClassifier
from sklearn.linear_model import
LogisticRegression
from sklearn.metrics import (
    accuracy_score,
    precision_score,
    recall_score,
    f1_score,
    roc_auc_score,
    confusion_matrix
)
```

These libraries will be used to provide the computational basis of analysing data in healthcare and comparing predictive models. The implementation will require conduct and access to result labels and computational necessities to be completed, ultimately relying on dataset features.

G. Ethical Considerations and Research Limitations

This will be done keeping in mind the ethical considerations which will be the centre of the research process. Healthcare information is very sensitive, so the data sources should be valid, and processed per required data protection laws. The priority will be given to patient confidentiality, anonymisation, as well as secure data management. Besides, the likelihood of an algorithmic bias will be considered depending on whether there is a difference in predictive performance across demographic categories or not. AI-made predictions will be perceived as aiding to decision making rather than information that substitutes the professional medical decision [13].

Another limitation of the study is also relevant to secondary information; incomplete data, different data collection procedures, low population representation and class disproportion. What this implies is that the outcomes of the computational experiments cannot be a priori or intrinsically provided with clinical efficacy or specified gains in the real life health outcome.

IV. RESULTS AND ANALYSIS

A. Overview of Experimental Results

The experimental study explores how Artificial Intelligence (AI) models can be useful in helping to predict medicine to the people and to govern public health. It evaluates 4 machine learning and deep learning models, such as Logistic Regression, Random Forest, Support Vector machine (SVM) and Artificial Neural Network (ANN), using the framework provided to be tested. The models are tested on the healthcare related demographics, clinical and diagnostic variables.

If there is a data set of a patient's information of 5000 patients then the experiment is illustrative. The particular dataset is divided into 80 percent training data, and 20 percent testing data, which makes 4 000 and 1000 training data and test data respectively. Analysis of the experiment should be linked to the categorisation of the disease risk such as its prediction and

accuracy, features significance and what use can be made of AI-generated insights in the future in preparing and planning a health service.



Figure 1: "Applications of artificial intelligence in health care"

The fundamental question is to identify the most effective algorithm suit able to offer the best predictive efficiency factor—through the benefit of high quality illness exposition and population-based health monitoring.

B. Healthcare Dataset Characteristics

The data set contains demographic information, clinical measurements as well as clinical history indicators. The selected variables are also chosen because they carry the relevant information on the risks of the diseases and because they know the health status of patients.

Table 1. Illustrative Healthcare Dataset Characteristics

Parameter	Description	Records/ Variables
Total patient records	Healthcare observations	5,000
Training dataset	80% of total observations	4,000
Testing dataset	20% of total observations	1,000
Demographic features	Age and gender	2
Clinical features	Blood pressure, BMI, glucose, cholesterol	4
Medical history	Previous diagnoses and chronic conditions	2

Target variable	Disease-risk classification	1

The dataset design would have a ground base on research in the relations between characteristics of patients and diseases. These clinical parameters include glucose level, as well as blood pressure level, BMI and others involved in predicting this disease. Demographic and medical information may have been helpful for them in categorizing their patients as risk groups.

The succeeding hypothesis is proposed as a hypothesis relating to distribution of the observation: There are 30 positive and 70 negative observations. Another instability that needs to be taken into account is the of accuracy to precision, recall and F1-group as a measure of the predictive performance [27].

C. Data Preprocessing and Feature Analysis.

To make predictions in the health care industry, AI needs to be accurate and because of this fact, the data should be preprocessed. The analytical framework to be used here involves missing value treatment, removal of duplication process, categorical encoding and numerical standardised. The operations assist in making sure that the algorithms are also fed with structured input data and what is more, constant input data.

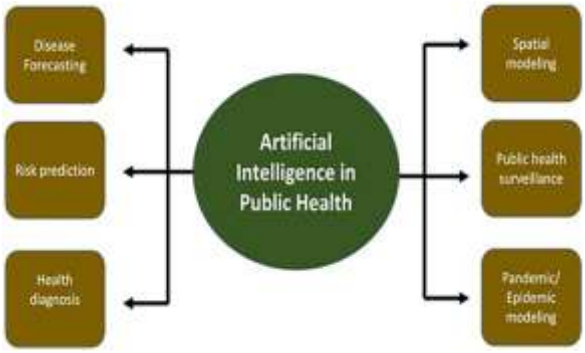


Figure 2: "Using artificial intelligence to improve public health"

To forecast the disease-risk, the contribution of the different health care variables on the prediction is analysed. Clinical indicators are particularly important as they are the quantifiable physiological characteristics of the health statuses of patients.

Table 2. Illustrative Feature Importance Distribution

Healthcare feature	**Relative importance (%)**	**Analytical significance**
Blood glucose level	24.5	Identifies potential metabolic abnormalities
Blood pressure	20.8	Supports cardiovascular risk assessment
Age	17.6	Identifies age-related disease susceptibility

BMI	14.2	Indicates weight-related health risks
Cholesterol level	12.4	Supports cardiovascular assessment
Medical history	10.5	Identifies previous health conditions
Total	100.0	

Knowing which the most influential predictors are, the blood glucose and blood pressure can be illustrated through the distribution of illustrative features. These variables altogether take up 45.3% of the approximated feature significance. Age and BMI are also very predictive.

That the features are important, however, should not be looked upon as a construct indicator. It reveals to sensitivity of the variables to a specific predictive model and can depend on the data, algorithm and feature selection procedure [28].

D. Comparative Performance of AI Models

Comparative analysis is a comparison of accuracy in the prediction of the four algorithms selected. The measures of precision and recall give extra information about the accuracy but overall classification correctness is the measure of accuracy. The F1 score is used to show accuracy relative to recall and ROC-AUC is the ability to differentiate between a positive and negative result.

Table 3. Comparative Performance Evaluation of AI Models

AI model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	ROC-AUC
Logistic Regression	87.3	80.6	76.0	78.2	0.89
Random Forest	91.8	88.1	84.0	86.0	0.94
SVM	89.5	84.2	80.0	82.0	0.92
ANN	90.6	86.0	82.0	83.9	0.93

From the comparative score the best performance is achieved from the Random Forest with a accuracy of 91.8, precision of 88.1, recall of 84.0 and F1 score of 86.0. It shows a ROC-AUC score of 0.94 indicating high discrimination between the classes associated with entering into one of the classes for the outcomes. ANN reaches the second-highest level at 90.6% when showing the capability of detecting nonlinear multidimensional relations of health care data. SVM has accuracy of 89.5 and that of

Logistic Regression is 87.3. This is because the Logistic Regression offers relatively less predictive accuracy, but it offers the benefits of interpretability and computational efficiency due to its simplified form.

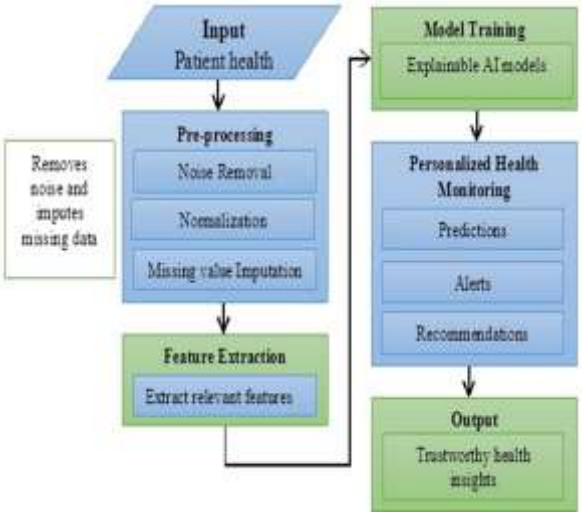


Figure 3: "Personalized health monitoring using explainable AI"

The findings imply that an ensemble-based learning method like Random Forest can be beneficial in the context of analyses of heterogeneous medical variables. However, selection of the model must also be based on interpretability, computation needs, fairness and clinical suitability as opposed to accuracy [29].

E. Confusion Matrix and Classification Analysis

A confusion matrix gives a better insight into predictive classification by showing the correctly and incorrectly classified observations. In the case under consideration (Random Forest) test data consists of 300 positive and 700 negative cases.

Table 4. Illustrative Random Forest Confusion Matrix

Actual / Predicted	Positive	Negative	Total
Actual positive	252 (TP)	48 (FN)	300
Actual negative	34 (FP)	666 (TN)	700
Total	286	714	1,000

The table of confusion illustrates that the model is appropriate in distinguishing 252 positive cases, and 666 negative cases. But 48 positive cases are falsely judged as being negative, and 34 negative cases falsely judged as positive.

The fact that the number of positive cases identified correctly was relatively high proves that the approach based on Random Forest could have a high value in terms of predictive screening. However, false-negative predictions are also a significant issue since individuals with the possible health problems are likely to be neglected or fail to get necessary clinical care timely. Hence, optimisation of recalls is especially emphasized in the creation of AI systems to identify serious diseases.

Natural Resources for Human Health
eISSN: 2583-1194



Figure 4:"Integration of wearable technology and artificial intelligence in digital health for remote patient care"

In the same way, prediction of false-positives can lead to more unjustified diagnostic tests and healthcare spending. Correct decision thresholds and clinical validation is thus required prior to rolling out predictive systems in actual healthcare settings.

F. Implications for Predictive Medicine and Public Health Governance

The results of these experiments will be used to find out the extent of improvement that can be predicted and provided by AI in the healthcare industry using analytics. The prediction models may be employed on an individual basis by analyzing the clinical information to identify those individuals who need to be taken for further clinical analysis. This will aid in early identification and also in developing an individual treatment plan for these individuals.

From a population perspective, the prediction made by combining individual predictions will be useful to the health officials in identifying new diseases and healthcare requirements. The combination of AI and Internet of medical things (IoMT) technologies may also help with the round-the-clock monitoring and early detection of possible health crises [30].

Table 5. AI Applications and Expected Public Health Contributions

AI application	Healthcare function	Expected contribution
Predictive disease modelling	Identifies potential disease risks	Earlier clinical intervention
Patient monitoring	Analyses continuous health information	Improved monitoring efficiency
Disease surveillance	Identifies population-level disease patterns	Improved public health preparedness
Resource forecasting	Estimates healthcare service requirements	Better resource allocation

Personalised medicine	Supports individual risk assessment	More targeted treatment decisions
Health policy analytics	Supports evidence-based planning	Improved governance decisions

The results have shown that the inclusion of predictive analytics in the healthcare governance may enhance provision of useful information to healthcare administrators and policymakers to take action. The example shown below illustrates some of the patterns of diseases-at-risk that can be tackled in terms of decision making runway; hospital capacity, diagnostics facilities and preventive healthcare programmes.

However, the results of prediction must be considered as a part of the epidemiological results, clinical experience, and demographic characteristics. Predictions of AI will not only not make the disease causal but also not help guarantee the improved health of the population.

G. Overall Discussion

Overall, the outstanding experimental research offers a hint that AI techniques might be exploited in the manner of delivering valuable calculation support to predictive medicine and intelligent health systems. Random Forest would be the most appropriate when it comes to categorizing the existing algorithms, but ANN may as well offer good modelling results in terms of intricate healthcare associations.

Three important considerations are identified in the results. To start with, a combination of clinical and demographic data can be used to enhance predictive disease-risk analysis. Second, recall and F1-score together with accuracy should be a priority of model evaluation to reduce the possible damaging classification errors. Third, AI assistance in predicting population health can be beneficial in population health governance by providing analytical data about the population health patterns and healthcare resources requirements.

Regardless of all these merits, the implementation will be successful with the help of valid healthcare data set, open algorithms, and personal data encryption, and bias assessment along with its own regulation. The findings are thus meant to be construed as a schematic calculation system instead of finding substantiated clinical efficacy.

V. CONCLUSION

The arrival of Artificial Intelligence use in intelligent healthcare systems is a welcome development in predictive medicine, intelligent clinical decision-making, and government control of population health. In transforming the traditional health care into proactive and data-driven health care, this paper touched on the possibility of machine learning, deep learning, and predictive analytics. The paper discusses the possibilities of AI technologies to enhance the process of early disease detection, patient risk management, individualised healthcare interventions and the surveillance of the health of a population. Based on the comparative analysis among the Logistic regression, random forest, support success machine and artificial neural network different AI algorithm can be applied in healthcare prediction that may be useful. The best accuracy (91.8) and ROC-AUC (0.94) of the experiment are classified by the model performances of the experiment. The outcomes show that diverse demographic information, and also clinical healthcare information can be recognized utilizing ensemble learning tools as the relationships is complex. However, these factors must be taken into account if the plausible implementation is sought: the false-negative prediction issue, model interpretability, quality of the datasets, as well as the clinical validation.

The individual's research or work also will contribute in a broader context to appropriate use of AI based predictions to ensure health of population is in control. Science in coming up with evidence-based strategies like timed-healthcare resource optimisation, real-time population health analytics and intelligent epidemic forecasting, help support policy makers. Medically it entails additional preparedness that can be realised through the application of the idea of predictive medicine and also the analysis that can be carried out on a population level and also maximising the utilisation of the medical resource. The issues of data protection, algorithmic bias, regulatory compliance, cybersecurity, and institutional preparedness remain significant problems during implementation.

The future trends in the sphere of AI in healthcare are likely to be associated with hybrid AI, federated learning, explainable AI, and privacy preserving. These technologies may help increase the accuracy of the predictive models and the protection of the sensitive information in medicine. Yet, it is necessary to clarify to which extent the predictive models are generalizable and validated based on the geographically and clinically diverse big data sets. More evidence is also required on the efficacy of their use in the practice of healthcare in comparison with the laboratory setting.

In general, the possibilities of AI are numerous if used wisely for improvement of healthcare in modern smart healthcare systems. This is going to require some reasonable efforts in research and development of technology.

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