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Research Article

Forecasting Healthcare Results in Rural and Resource-Limited Settings Using the Machine Learning Algorithm

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ABSTRACT

In this research, we investigate machine learning (ML) application in the healthcare domain we predict obesity, perinatal mortality, diabetes risk assessment, and how to integrate blockchain into healthcare. It shows ML promising to increase disease prediction, optimize the policies of healthcare, and secure the data. ML is highly predictive accurately though it suffers from interpretability and fairness challenges. To achieve the equitable healthcare outcomes, future works need to develop better models for causal inference and embed the ethics in the process.

Keywords: Healthcare, ML, AI, Rural.

1. Introduction

Machine learning (ML) is helping practice of healthcare by giving predictive analytics in disease risk, patient outcomes, and public policy. In this study, ML is used in obesity prediction, perinatal mortality, diabetes classification, and blockchain integrated healthcare. ML is limited by bias, data security and interpretability. Immunizing a child has higher predictive accuracy and we can use it to understand how should we respond based on data.

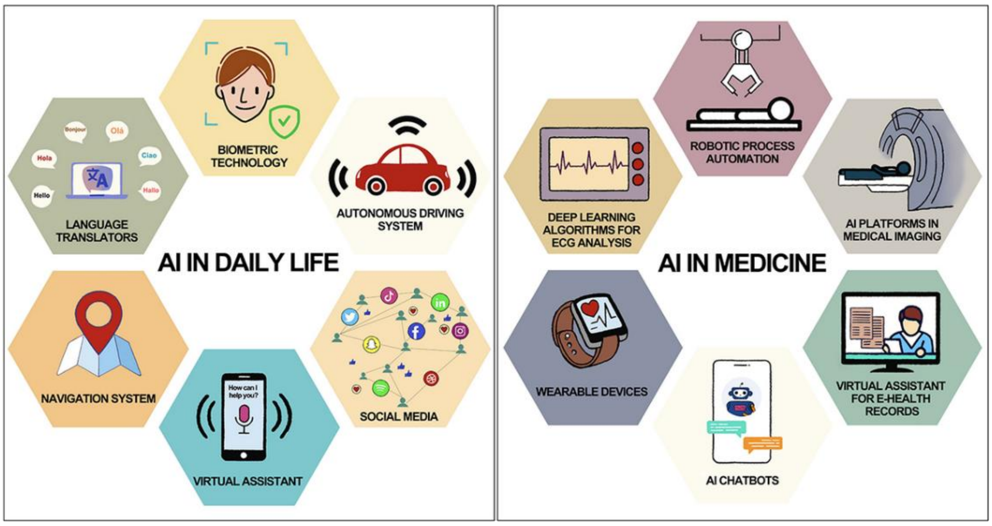

Figure 1: AI in Medicine (Frontiers, 2023)

4. Literature Review

Machine learning (ML) has been deemed as a game changer in healthcare by providing the answer to solving diagnosis, treatment, and patient outcome problems, especially in rural and resource limited areas.

With time, ML algorithms took role in healthcare as there is disease prediction, nutritional status assessment, maternal and child health outcomes, and healthcare communication. In this literature review, key contribution in this domain is explored based on existing studies that identifies the trends, challenges, and future directions.

1.1 Machine Learning Applications

We have seen that ML algorithms can able to explore large datasets and apply it for disease detection, diagnosis, and treatment monitoring. AI models can help in the early diagnosis of the disease, constant checks for the patients suffering from chronic disorders and projecting the public health aspects according to Mbunge and Batani (2023).

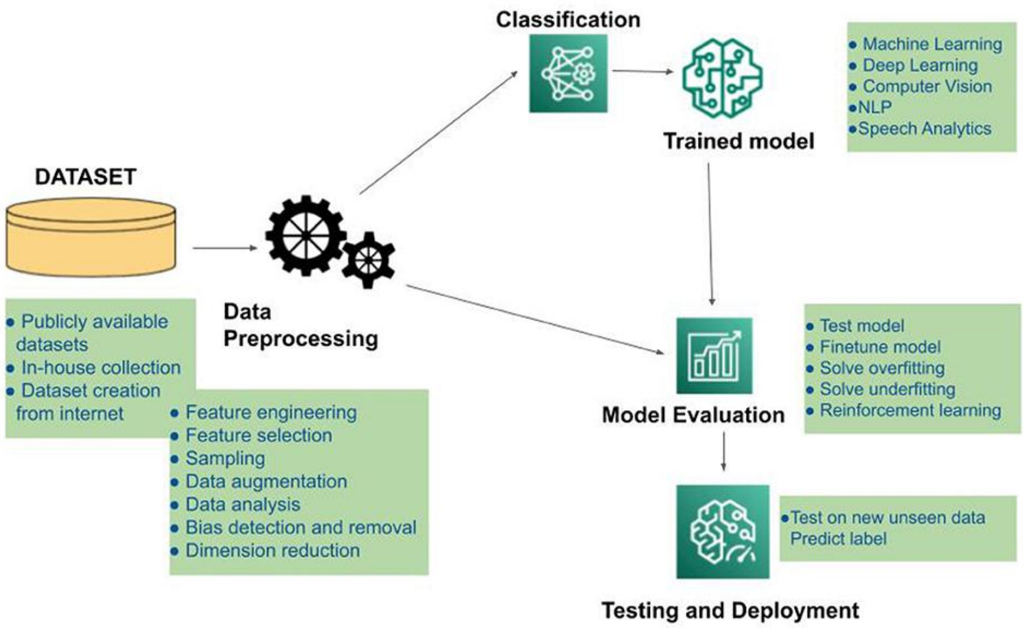

Figure 2: Maternal Health AI Models (Frontiers, 2022)

Integrating ML based solutions into the healthcare systems is limited due to challenges. Bitew et al. (2022) had studied the prediction of childhood undernutrition in Ethiopia by applying various ML models like eXtreme Gradient Boosting (XGB), k-Nearest Neighbours (k-NN), and random forest.

The result shows that XGB is more powerful than other algorithms and with this we find that factors such as access to clean water, maternal health and food security affect greatly child nutrition outcomes. This suggests that ML can yield highly precise predictive models for specific interventions among rural health.

Raja et al. (2021) developed risk prediction conceptual model (RPCM) for prediction of preterm birth (PTB) in rural India. The study used decision trees, logistic regression, and Support Vector Machine (SVM) and has found that SVM has performed with the highest accuracy of 90.9%. This shows the importance of ML in maternal healthcare specifically where traditional diagnostic methods are not adequately or not at all available.

1.2 Public Health Issues

Increasingly, the public health concern such as malnutrition, infant mortality are increasingly being addressed using ML methods. In Islam et al. (2022), the recommendation considers treating malnutrition among women in Bangladesh using ML classification models, to predict based on the predictors of malnutrition.

It was found that random forest model yielded highest accuracy for the forecast of underweight and overweight/obesity cases, and hence ML proved a key tool to predict high risk patients and support nutritional interventions.

Like Mfateneza et al. (2022), the investigation of ML based predictive models for Infant mortality in Rwanda was also similar. To predict infant mortality risk; four ML classifiers such as Random Forest, Decision Tree, SVM, and Logistic Regression were applied on in the study.

The most effective model out of 16 based on accuracy was random forest with 84.3 accuracy which further demonstrated the role of ML in inferring key determinants of infant survival like maternal health, socio economic status and the access to healthcare services.

One other dimension of ML's impact on public health is in climate related health studies. In Berrang Ford et al. (2021), ML techniques were used to develop a systematic understanding of the conditions through which climate change influences human health.

Supervised learning and natural language processing was used in the study to map global trends in research for climate driven health risks including malnutrition, maternal health, infectious diseases. The results emphasize the significance of continuing ML driven research to tackle climate induced health crises in resource deprived areas of the world.

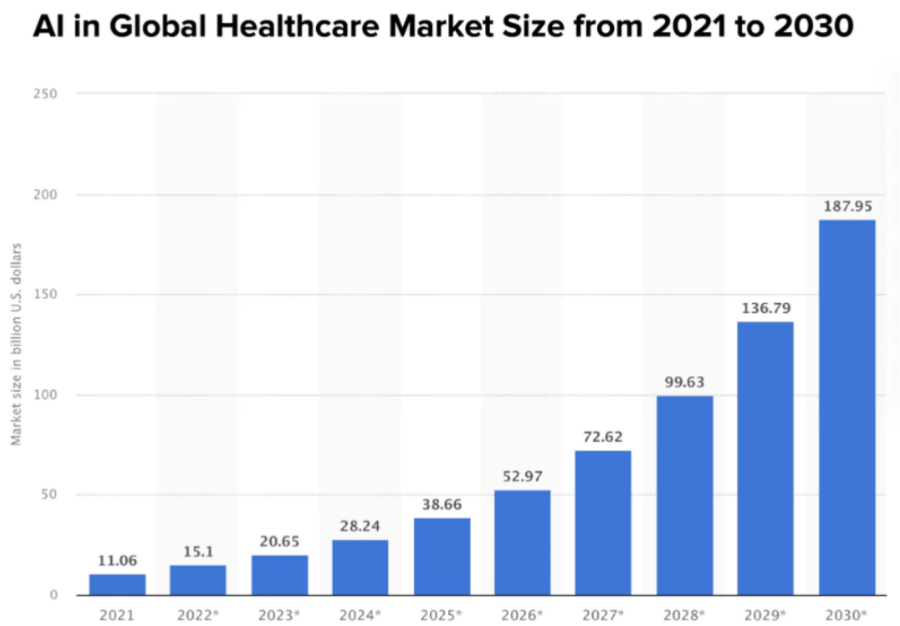

Figure 3: AI in Healthcare Market (Appinventiv, 2025)

1.3 Healthcare Communication

Apart from the predictions of disease and public health monitoring, ML is altering the manner in which healthcare communicates. According to Siddique and Chow (2021), they investigated the potential of ML in improving healthcare dialogue management, for example, by using AI powered chatbot. The real-world deployment has been successfully done across these such areas that include COVID-19 health education, cancer therapy assistance, and medical imaging analysis.

In rural locations where health care access has limitations, ML driven chatbots can act as a key device of patient education and involvement. This can further help to integrate ML into decision-support systems for healthcare delivery.

In their perspective (Mbunge and Batani, 2023), AI driven analytics can assist healthcare professionals in enhancing diagnosing accuracy, making them allured treatment decisions, and also drug development. Despite this, there are several issues, such as data and infrastructure limitations and ethical concerns, which must first be addressed if you are to make the most of the impact of ML in the rural healthcare setting.

1.4 Future Directions

However, there are still numerous challenges to overcome for the applications of ML in healthcare. As identified by Mbunge and Batani (2023), however, there is a limit in the biases that stem from AI algorithms due to incomplete, or not representative datasets. Data from high income regions are many a times used to train many ML models, and they do not reflect healthcare realities in rural and low resource settings.

Furthermore, the failure to integrate ML based solution into healthcare systems due to the lack of structured health data and interoperable frameworks. As Raja et al. (2021) noted, many previous ML models do not take into consideration region-specific differences in maternal health indicators, and as such are not very generalizable.

Infrastructure constraints such as reduced internet connectivity, poor computing power, and poor training of healthcare workers in ML applications are the other challenge faced. As Berrang-Ford et al. (2021) state, there is a disproportionate focus on climate related health research in high income countries, leaving space for ML generated health solutions for rural and low-income regions.

- Training ML model on diverse and diverse datasets for each of the developing region.
- The way to improve the data collection mechanisms via digital health initiatives.
- Numerous AIs wind up on the market among scrupulous companies, offering healthcare companies to improve AI and ethical questions.
- Improvement of AI related policies and frameworks for health care.

Consequently, by addressing these challenges, the potential exists for ML to radically change healthcare delivery in resource and rural settings to enable improvements in patient outcome and resources healthcare allocation.

Table 1: Key findings

Study	Focus Area	Key Findings	ML Techniques Used
Mbunge & Batani (2023)	AI in SSA healthcare	Diagnosis, monitoring and disease prediction can be improved with the help of AI, but there are lots of issues to do with bias and lack of policy around it.	Deep learning, ML models
Bitew et al. (2022)	Childhood undernutrition	Other algorithms were out predicted for risk factors of undernutrition, however, XGB algorithm performed better than the rest.	XGB, k-NN, RF, Neural Networks
Raja et al. (2021)	Preterm birth prediction	In PTB classification, SVM also achieve 90.9% accuracy	SVM, Decision Tree, Logistic Regression
Siddique & Chow (2021)	Healthcare communication	Uses made of ML chatbots to help patients and train them	AI-driven dialogue management

Mfateneza et al. (2022)	Infant mortality prediction	In Rwanda, RF was the most suitable predictor of IM	RF, Decision Tree, SVM, Logistic Regression
Islam et al. (2022)	Malnutrition prediction	And the RF model accurately classified malnourished women	RF, Decision Tree, Naïve Bayes, ANN
Berrang-Ford et al. (2021)	Climate change and health	Global evidence on the climate health impacts was synthesized by ML	Supervised ML, NLP, Topic Modeling

However, it does offer great promise in improving the healthcare outcomes in the rural and resource limited settings. ML driven approaches are transforming the realm of health care delivery from the disease prediction to the public health intervention and health care communication.

However, such challenges as biased datasets, insufficient infrastructure, and absence of AI policy must be overcome if ML has the full potential to be done in these settings. To realize more from ML in rural healthcare, future research can be oriented towards developing region specific models; merging AAIs and AI in an ethical way; and having stronger infrastructure for digital health.

2. Methodology

In this research, the methodology used is systematic literature review to synthesize existing studies on predicting healthcare outcomes in the rural and resource limited settings with machine learning algorithms. These are all reviewed through seven of the peer reviewed studies involved in the application of artificial intelligence (AI) and machine learning (ML) in healthcare in such low resource environments.

The chosen studies are those that pertain to the research topic, emphasize predictive modeling, healthcare accessibility and algorithm performance in medical diagnosis and public health intervention.

Studies reviewed focused on applications in sub-Saharan Africa, Ethiopia, India, Rwanda and Bangladesh in the areas of child undernutrition, preterm birth prediction, malnutrition in women, infant mortality and impacts from changes in climate on health.

The methodology of this paper consists of identifying the key contribution, trends and gaps in the literature as well as the potential of ML based models in improving healthcare decision making.

Moreover, the challenges of data availability, algorithmic bias and ethical matters are discussed at hand to comprehend the boundaries of incorporating AI in the resource sparse healthcare system. Based upon these findings it can be concluded that this literature review lays the ground work needed for further research and policy recommendations with regard to transparency, data driven education, as well as improved AI model implementation to aid healthcare progress in under developed areas.

3. Findings

Machine learning integration in healthcare has positively impacted the prediction of health outcome, risk assessment optimization and influential determinants of diseases.

It is a synthesis of various studies to showcase how ML models are being used successfully in healthcare, in resource restricted environments. The studies analysed show how much the use of ML is increasing in response to health disparities, chronic diseases predictions, and clinical decision making.

The results show that ML based solutions outperform the traditional statistical techniques by being able to handle the nonlinear relationships among multiple predictors and get better accuracy and better generalizability. However, the contribution of the others involves data bias, model interpretability or ethical concerns.

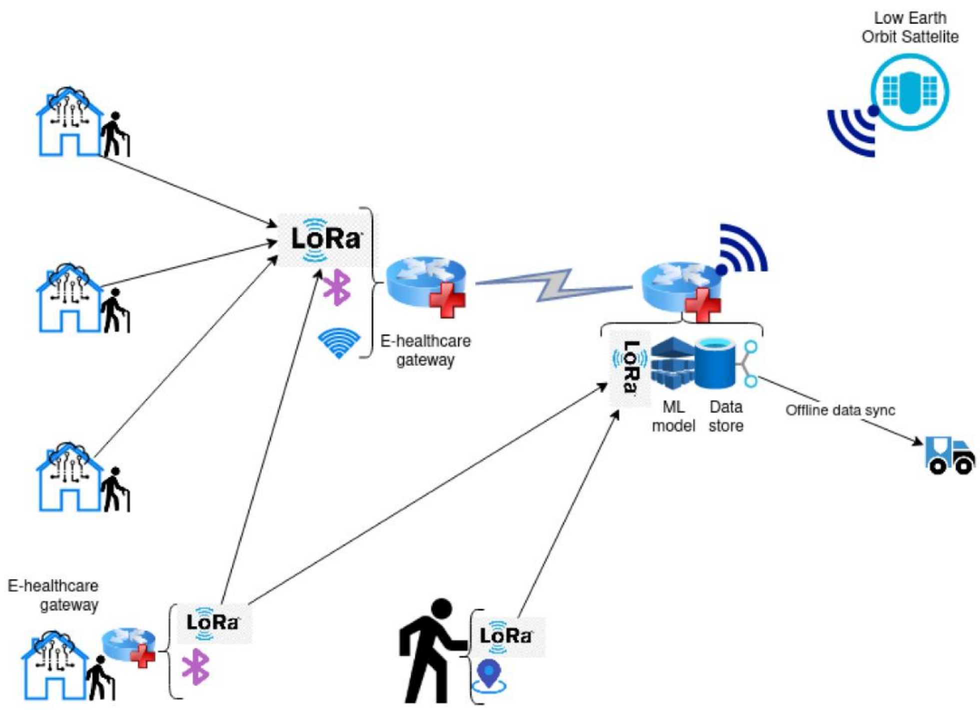

Figure 4: Rural IoT architecture (MDPI, 2021)

3.1 Predicting Obesity

Obesity is a significant world health problem with several risk factors for its development. Thamrin et al. (2021) mentioned that Logistic Regression, Classification and Regression Trees (CART), and Naïve Bayes are some of the ML models used to predict obesity from some publicly available health datasets.

Logistic Regression proved to be the highest predictor in predicting obesity based on the study. Located risk factors were such as the location, marital status, the age, the education, and dietary conditions like sweet drink, fatty oily foods, and carbonated foods. Additionally, lifestyle behaviours, including smoking, alcohol intake and physical activity, also explained accurately the association with obesity.

The data imbalance was solved by Synthetic Minority Oversampling Technique (SMOTE) in this study as well as enhancing the model robustness. The findings indicate that ML can be used to analytically examine complex health data to enable policymakers to take control over obesity related health risk.

3.2 Perinatal Mortality

Even in Ethiopia, where perinatal mortality rate is among the highest in Africa, Bogale et al. (2022) explored the application of ensemble ML methods for the prediction of the mortality rate. The Random Forest, Gradient Boosting and Cat Boost algorithms were used to create predictive models and Gradient Boosting provided the highest accuracy of 90.24%.

The study attributed major contributors to perinatal mortality to financial constraints, home delivery and lack of health insurance. Feature importance analysis identified important predictors such as maternal education and anaemia levels, as well as factors related to the region, place of residence and birth interval.

It was able to show the potential of ML in being able to identify at risk pregnancies and provide early interventions. Such predictive models can be implemented in healthcare systems to significantly decrease maternal and infant mortality rates particularly in low resource setting.

This following Python snippet depicts how a Gradient Boosting can be used for the healthcare prediction tasks as done by Bogale et al. (2022).

```python
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
import pandas as pd

# Load dataset
data = pd.read_csv('health_data.csv')

# Splitting dataset into features (X) and target variable (y)
X = data.drop(columns=['perinatal_mortality'])
y = data['perinatal_mortality']

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Initialize and train the Gradient Boosting model
gb_model = GradientBoostingClassifier(n_estimators=100, learning_rate=0.1, max_depth=3)
gb_model.fit(X_train, y_train)

# Predictions
y_pred = gb_model.predict(X_test)

# Model accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f'Gradient Boosting Model Accuracy: {accuracy:.2f}')
```

3.3 Diabetes Prediction

Diabetes is one of the biggest chronic diseases in the world that can cause severe complications to the health. In their work, Ahmad et al. (2021) tested various types of ML classifiers in predicting diabetes and how HbA1c and FPG as input features would perform in comparison. The study proved that the ML based prediction models could possess high accuracy, recall, precision, in different classifiers and in general, satisfy the performance metrics consistency.

Figure 5: Healthcare in rural sector (Healthcare IT News, 2018)

The research analyzed feature importance and determined the key risk factors for diabetes in accordance with the American Diabetes Association guidelines. On a cost-efficiency basis, it (the study) demonstrated the cost advantage of ML driven diabetes screening, easing burden from healthcare system. Using ML models in routine clinical practice would make it possible to improve early detection and management of diabetic patients.

3.4 Logistic Regression Model

Logistic regression itself is a key method for disease prediction based on independent variables in order to predict the probability a disease will occur. Coefficients in the formula of the logistic regression model are given below.

$$P(Y=1) = 1 / (1 + e^{-(\beta 0 + \beta 1X1 + \beta 2X2 + \ldots + \beta nXn)})$$

where:

- $P(Y=1)$ is the probability
- $\beta 0$ is the intercept.
- $\beta 1, \beta 2..., \beta n$ are the coefficients of independent variables $X1, X2..., Xn$.
- e is the base of the natural logarithm.

The use of this formula allows for estimating of disease probabilities given various patient attributes to further aid clinical decision making.

3.5 Smart Healthcare

Machine learning and blockchain (BC) technologies are the new revolution that brought security, decentralization, and data-based health solutions in the healthcare industry. In a bibliometric review of the literature of ML and BC integration in the healthcare setting, Li et al. (2021) identified several factors that ML algorithms share with BC practice.

The study identified research hotspots, funding trends, key applications as well as comment on the five major themes that have emerged from the related intersection of these technologies. While ML provides the predictive capability, blockchain is being used for the security, transparency, and integrity of data in smart healthcare system.

The findings indicate that ML-BC can enhance the data interoperability, privacy of patients and provides a basis for the end centralization of the decision making in healthcare services. Problems associated with scalability, regulatory compliance and computation overhead have to be overcome to realize the full potential of such technologies.

This research findings also point out the transforming part of using machines learning in healthcare and predicting diseases or optimising the health results. The studies reviewed show that there is a higher accuracy and risk assessment achieved using ML models compared to traditional statistical methods.

Although such challenges need to be resolved for effective implementation, their related strategies, such, as data bias, ethical issues, and model interpretability, are also discussed. It further suggests that future research integrate ML into emerging technologies such as blockchain to increase the security and efficiency in the healthcare systems.

ML can be used to build better intervention strategies based on disease prediction and this will enable policymakers and healthcare professionals to improve public health outcomes worldwide.

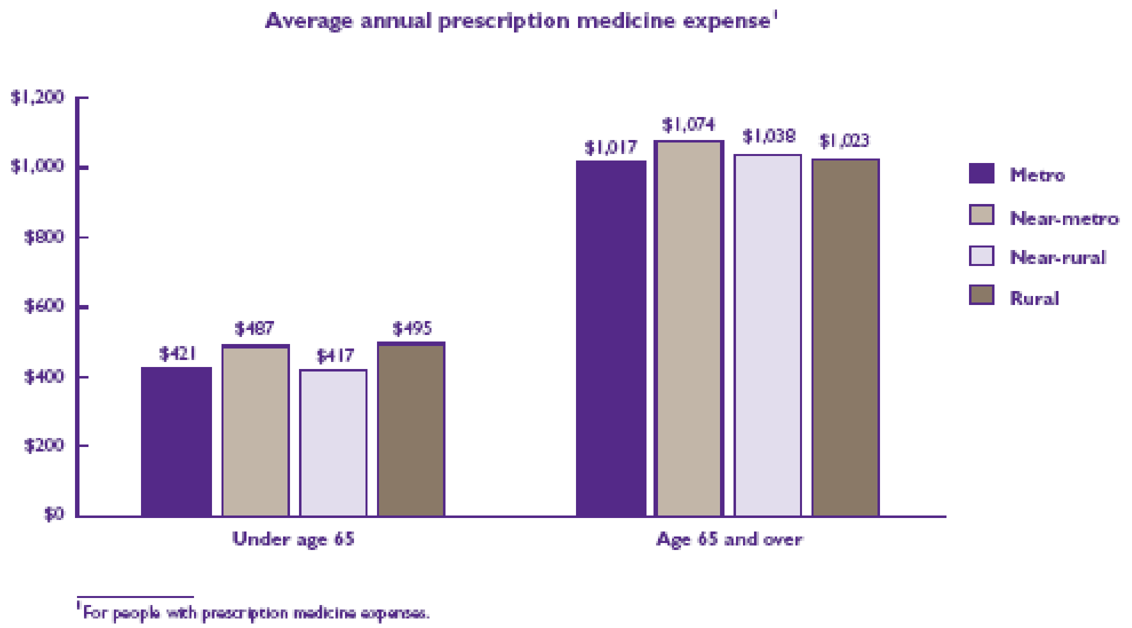

Figure 6: Healthcare in rural and urban sector (MEPS, 2023)

4. Discussion

Applying machine learning (ML) in healthcare research has grown larger and larger, with the ability to predict health outcomes, understand the risk factors of disease, and enhancing some of healthcare services.

In this discussion, we synthesize findings from many studies, address common themes, methodologies, and implications in so far as obesity, perinatal mortality, social determinants of health (SDH), diabetes prediction, and integration of ML with blockchain technology.

4.1 Predictive Analytics

Prediction of health risks based on many variables is one of the most compelling applications of ML in healthcare. Thamrin et al (2021) used ML technique like Logistic Regression, Classification and Regression trees (CART) and Naive bayes to predict obesity risk factor.

In addition, they found that Logistic Regression was best but ML models still performed well at predicting. This study was able to identify several risk factors, including dietary habits and physical activity levels as well as mental health conditions, which contribute to obesity to a great extent.

The Synthetic Minority Oversampling Technique (SMOTE) was also applied in the study to handle the data imbalance problem, which is a predominant issue in the realm of predictive analytics. Much like in Bogale et al. (2022), ML was used to predict perinatal mortality in Ethiopia, and ensemble learning techniques, such as Cat Boost, Random Forest, and Gradient Boosting, showed the effectiveness of it when applied.

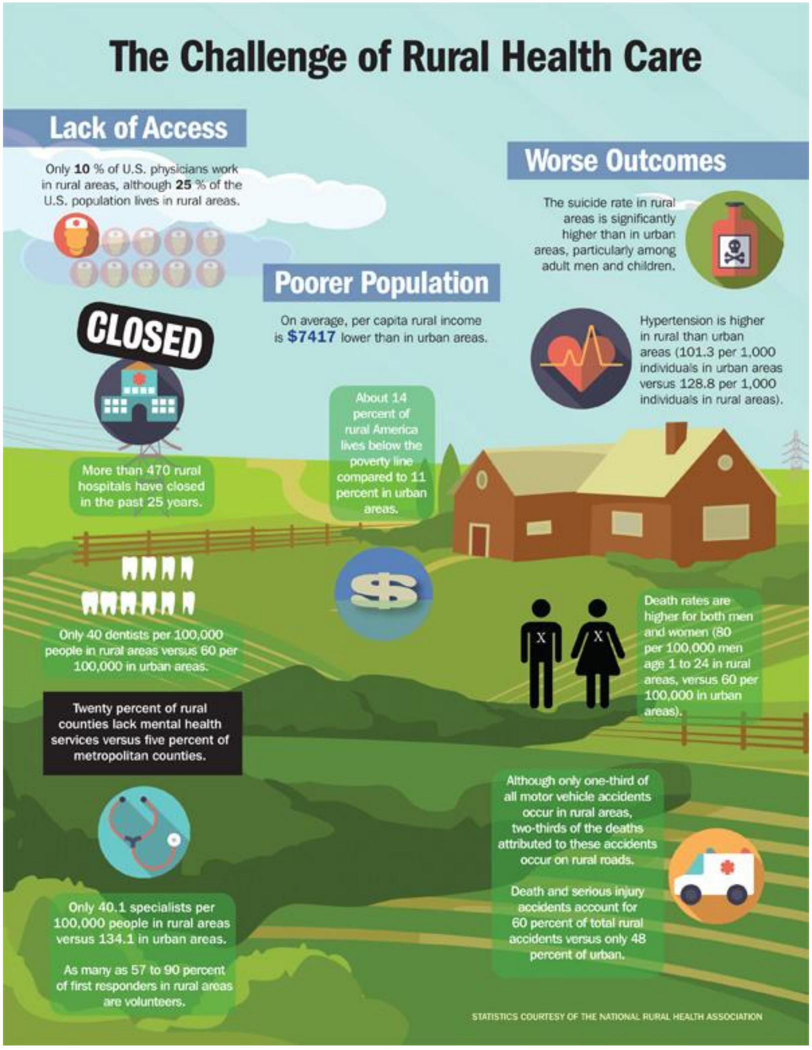

Figure 7: Challenges in Rural healthcare (IEEE, 2016)

However, they found that community-based health insurance, maternal education, preterm birth and anaemia levels were determinants of perinatal mortality. Secondly, Gradient Boosting model displayed the highest accuracy (90.24%) and so, it tends to be a favourite for risk analysis and predictive modelling.

The study also highlights how implementation of ML can have actionable insights in maternal and child health that can be helpful to policymakers in intervention design. Kino et al. (2021) did a broader review and found that ML is being increasingly used in social epidemiology, but its uses are still narrower in terms of being deployed to predictive tasks rather than causal inference or data curation.

With the promising capacity of ML to analyze non-traditional data sources such as text, audio, and images, the results indicate that most research continues to derive from surveys. This implies that sophisticated prediction techniques offered by ML improve prediction accuracy but have yet to be fully exploited to understand the causes underlying these health disparities.

In this work, taken by Ahmad et al. (2021), in which they focused on diabetes prediction and compared different ML classifiers and studied the predictive power of the levels of HbA1c and FPG. They validated their work; based on that, ML models were able to accurately categorise diabetic and prediabetic individuals with high precision.

By choosing only a subset of the most relevant features, the research showed that diabetes could still be screened at a low cost and in a relatively short time as compared to the regular screening process, thus sparing healthcare systems the corresponding high-cost need. The findings conform to recommendations from the American Diabetes Association that help ML in identifying diabetic risk factors.

4.2 Emerging Technologies

Another area of application of ML with BC technology concerns healthcare, and it goes beyond individual disease prediction. In Li et al. (2021), they studied the new field of "smart healthcare" that aid in creating more secure, transparent, and efficient healthcare services through ML and BC.

Deep analysis of their bibliometric shows that what they found was patient data security, decentralized medical records, and AI-driven diagnostic. The study also highlighted the fact that ML enhances predictive accuracy but BC guarantees the data integrity and trustworthiness thus resolving critical challenges faced by sector in the digital healthcare transformation.

4.3 Public Health

These studies provide results that show the potential by ML to alter public health research and public health policy making. Thamrin et al. (2021) showed how obesity prediction models can assist health authorities to improve rationality in the policy of preventing chronic disease.

Bogale et al. (2022) argued for the impact of financial incentives like health insurance on reducing perinatal mortality for reasons of having policy interventions that target would improve maternal and child health outcomes.

According to Kino et al. (2021), ML strengthens data analysis powers but explores the using of ML to understand social determinants of health. 'One thing that this study taught us was the need for ML to move beyond predictive modelling and to interact with hardware to measure for instance something related to algorithmic fairness or bias detection.'

That is in line with Li et al. (2021) who claimed that blockchain integration will mitigate ethically concerned issues in healthcare applications using ML by improving transparency and security. The feature selection role plays another important aspect when it comes to choosing the most optimal predictive accuracy. In their work cited by Ahmad et al (2021), hierarchical clustering and feature permutation were used to identify the most relevant predictors for diabetes.

The reduction in unnecessarily diagnostic tests and healthcare costs was demonstrated by their research that showed even a very limited set of biomarkers could provide high prediction accuracy. Healthcare research benefits from the integration of ML in predicting and assessment of diseases, risk, and policy formulation.

The studies reviewed illustrate how ML can improve predictive accuracy in health; early identification of obesity, for example, and perinatal mortality; diabetes and general social determinants of health. The synergy of Blockchain and ML technology not only draws over these with the potential for empathetic, secure, transparent, and efficient healthcare services, but also entails the emergence of new technological frontiers for adoption in both care and medicine among other realms.

While ML does extremely well for predicting, its application to causal inference and fairness is still heavily challenging. Future research should expand its focus toward more interpretable ML models, more multitude in data sources and placing ethical considerations into its core for an equitable healthcare outcome.

Using the power of ML to enter the state of predictability and the presence of emerging technologies, health systems can become more proactive, personalized, and efficient to fight against global health challenges.

5. Conclusion

With the revolution of ML, healthcare prediction disease, health policy optimization, as well as in Blockchain medical data integration, is revolutionizing healthcare. ML as a field is studied for obesity, perinatal mortality, and diabetes prediction, and measures to improve public health can be taken from these studies. To optimize ML models' potential for equitable and efficient healthcare solutions, future research should refine the themselves as well as make them perhaps even more transparent while also making sure that they are doing so in fair and ethical ways.

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