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Research Article

AI-Assisted Diagnostics for Rural and Underserved Communities: Bridging Healthcare Gaps

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ABSTRACT

The delivery of quality healthcare in rural and other hard-to-reach areas in the United States remains a challenge due to inadequate infrastructure, a shortage of healthcare workers, and limited funding. These barriers lead to late diagnosis, worse health and a large disparity in health care. This research aims to identify the process of developing and implementing cost-effective diagnostic AI systems that are specifically designed to identify chronic and critical diseases, such as diabetes, skin cancer, and influenza, in these areas. The tools employed include machine learning algorithms, portable diagnostic devices, and cloud-based analytics. They showed high diagnostic accuracy with sensitivity of up to 94% for diabetes diagnosis and 91% for skin cancer diagnosis. Another important improvement was the cost efficiency, which was noted as the fact that the AI-based methods were, on average, 45% cheaper than conventional methods. Moreover, the use of AI-supported tools enhanced early detection by a large margin, especially in Appalachia; early diabetes identification rose from 40% in 2019 to 78% in 2023. Nevertheless, some of the issues highlighted include restricted internet connections, legal restraints, and initial rejection from the medical fraternity. Solving these problems will require infrastructure development, changes in the law, and trust in new technologies. This paper focuses on the role of AI Diagnostics in filling gaps in healthcare for special populations in the United States. In this paper, AI technologies are argued to be a scalable solution to address the equity issue and enhance healthcare for rural populations through reduced access costs and improved diagnostic capabilities. Telemedicine tools for self-monitoring should be developed for other conditions and incorporated into other telemedicine solutions.

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1. Introduction

1.1 Background and Importance of the Research

For this paper, health and social care will be discussed in the context of inequality and as one of the systemically important social and economic problems of the United States. As Sosin and Carpenter-Song (2024) research indicates, rural and underserved populations make up a large part of the United States population, and these are the most at risk from healthcare inequity. These areas, most often in very remote locations with no or limited access to Hospitals, clinics or any form of health care, have a population largely of geriatrics, and the most affected are in chronic diseases, late diagnosis and minimal preventive care. This means that this difference creates imbalances not only in terms of the general health of people but in the socio-economic field as well, which implies the growth of emergency service demand and decreased efficiency rates. The requirement to address such disparities has only become more urgent, with COVID-19 revealing the vulnerability of the healthcare system in the US, particularly in rural areas (Fulmer et al., 2021). For instance, the ability to handle patient flow was a problem that revealed many rural hospitals' ongoing and fundamental structural and personnel challenges. On the same note, other diseases, including diabetes, cancer, and cardiovascular diseases, have also continued to

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contribute to morbidity and mortality in these regions (Schopfer, 2021). Solving these problems requires going outside of traditional medical models of care delivery. Of these strategies, Artificial Intelligence (AI) is a helpful approach to counter these gaps. This is a great potential of AI that has the potential to transform the delivery of health care in rural and other inaccessible regions by offering a quick, accurate and affordable diagnosis (Iqbal et al., 2023). The goal of this work is to develop and apply artificial intelligence-based diagnostic tools for primary and relapsing diseases and health states and to achieve improvement in the accessibility of high-quality medical care for the population of the United States.

1.2 Current Issues on Access to Healthcare

The issue of affordable and effective health care is still present in contemporary America, as millions of people from rural and other underserved areas cannot afford proper medical care (Coombs et al., 2022). Some of the factors that contribute to this disparity include:

i. **Geographic Barriers:** Residents of rural areas do not have easy access to health facilities; they have to travel long distances to seek routine or specialized care. For example, a patient in a rural area of Appalachia may have to travel several hours to receive endocrinology for diabetes.

ii. **Workforce Shortages**: The healthcare workforce shortages in rural settings include general practitioners, specialists, and nurses. According to the National Rural Health Association (2024), there are 13.1 physicians per 10,000 populations in rural areas, while the figure is 31.2 in urban areas.

iii. **Financial Constraints**: Most residents in such regions are either uninsured or cannot afford the cost of their health care, which keeps them away from hospitals.

iv. **Technological Gaps**: Poor broadband connectivity in rural areas also slows the use of telehealth and other digital health systems, which in turn excludes these areas from accessing other advanced healthcare services.

1.3 The Role of AI in Mitigating These Challenges

The world now understands that AI is a disruptive technology that has the potential to transform many industries, and healthcare is not spared. AI can perform a mass of medical data, recognize disease signs, and select an individual treatment approach in a short time.

i. **Enhancing Diagnostic Accuracy:** The diagnostic application with machine learning algorithms is capable of identifying relatively subtle deviations in medical images, laboratory results, and patient files. For instance, convolutional neural networks (CNNs) have been used to diagnose skin cancer with the same accuracy as that of board-certified dermatologists.

ii. **Improving Accessibility:** The mobility of biosensors and others, such as smartphone-based imaging and wearables, can transport diagnoses to patients in such facilities. This cuts down the reliance on big centralized laboratories and special facilities, thus enhancing access to health facilities.

iii. **Cost-Effectiveness:** By the automation of many processes and the inapplicability of costly machines and professional services, the costs required for diagnostics can be significantly reduced by AI. For instance, portable glucometers enhanced with artificial intelligence are capable of conducting on-spot diabetes tests effectively and at a much lower cost than testing in laboratories.

iv. **Empowering Providers and Patients:** AI can help overwhelmed healthcare workers by taking up some of their time through tasks such as translating diagnostic results. These instruments provide patients with useful knowledge of their state of health and encourage them to play a more active part in disease control.

2. Materials and Methods

2.1. Development of AI Diagnostic Tools

When developing AI-based diagnostic tools for the targeted communities in the USA, it became crucial to address the issues of tool cost, portability, and invasiveness. The tools were developed using ML algorithms based on extensive data sets, which are characteristic of rural populations, such as Diabetes, cancer, and infectious diseases.

2.1.1 Model Architecture

i. **Chronic Conditions (e.g., Diabetes):** The gradient boosting algorithms and logistic regression models were used to predict the likelihood of Diabetes given inputs such as HbA1c, age, BMI and family history of Diabetes. These models were originally designed for low-processing-power platforms and are well-optimized for portable platforms.

ii. **Image-Based Diagnostics (e.g., Skin Cancer):** CNNs were used to analyze images of skin lesions taken by smartphones with an accuracy comparable to that of dermatologists.

iii. **Infectious Diseases (e.g., Influenza):** Recurrent Neural Networks (RNNs) predicted the likelihood of infection based on patient symptoms, temperature, and historical flu cases.

2.1.2 Hardware Integration

The following diagnostic tools were designed for use with accessible hardware:

i. Chronic disease screening and monitoring devices include portable glucometers and blood pressure monitors.

ii. Mobile imaging devices that incorporate artificial intelligence for diagnosing skin and tissue pathologies.

iii. Smart clothing, including wristbands with biosensors, monitors real-time physiological parameters such as temperature and pulse rate.

2.1.3 Cloud-Based Analytics

Due to connectivity issues in rural areas, hybrid processing models were used as tools. Data was primarily analyzed at the site to provide initial findings, with additional calculations performed in HIPAA-compliant cloud systems when network connections were available.

2.2 Data Sources and Preparation

The development and training of AI models relied on comprehensive datasets representative of the U.S. population.

2.2.1 Data Acquisition

i. Chronic Disease Data: Electronic medical records from the CDC's National Health and Nutrition Examination Survey (NHANES) were utilized to train the models for predicting diabetes and hypertension risk.

ii. Cancer Imaging Data: The NCI database contained 900 high-resolution dermoscopic images of skin lesions.

iii. Infectious Disease Surveillance: Data on symptoms and outbreaks were sourced from the CDC FluView Interactive and other records from state health departments.

2.2.2 Data Cleaning and Pre-processing

Data preparation involved:

i. Data cleaning filters out noisy data, eliminates redundancy, and makes training sets as accurate as possible.

ii. Standardizing parameters such as blood glucose levels and lesion size.

iii. Labels generated by board-certified healthcare professionals are used to accurately label medical images.

2.2.3 Bias Mitigation:

To mitigate the bias in the datasets, some attempts were made to include minority races and groups with low socioeconomic status. Oversampling and synthetic data augmentation strategies were applied to address the imbalance in the datasets.

2.3 Pilot Deployment

To validate the tools, pilot programs were conducted in three regions with distinct healthcare challenges:

2.3.1 Appalachia (Diabetes and Hypertension Screening)

The AI-assisted glucometers were used in conjunction with mobile clinics. Screening sessions were aimed at those above 40 years of age, a group known to have high rates of diabetes.

2.3.2 Southwest U.S. (Skin Cancer Diagnostics)

Clinics that offered services to people frequently exposed to UV radiation were able to access imaging tools, such as smartphones. The community health workers were trained on how to take skin lesion images and analyze them with the help of AI tools.

2.3.3 Mississippi Delta (Flu Detection)

Wearable devices were provided during the flu season to track symptoms and detect signs of onset. All findings were disseminated to the specific county health departments to guide their decision-making.

2.4 Evaluation Metrics

The performance of AI tools was assessed using the following metrics:

2.4.1 Diagnostic Accuracy

For each use case, sensitivity, specificity, and area under the ROC curve were provided.

2.4.2 Cost Efficiency

The cost of using the AI tool was established and compared with the standard diagnostic techniques including laboratory tests and consultation with the specialists.

2.4.3 User Acceptance:

Self-administered questionnaires and face-to-face discussions with the healthcare providers and patients assessed usability, confidence in the results generated by AI, and satisfaction.

2.4.4 Scalability:

The opportunity to apply the tools in other rural areas was evaluated in terms of pilot program results.

2.5 Statistical Analysis

Data collected during the pilot programs were analyzed using statistical tools in Python and R. Key analyses included:

i. **ROC Curve Analysis**: To compare the diagnostic performance for different thresholds.

ii. **Cost-Benefit Analysis**: To measure the economic benefits that may result from implementing the use of artificial intelligence.

iii. **Thematic Analysis of Feedback**: Interview data were analyzed and categorized to develop themes, which include the benefits of AI technology and perceptions about the same.

2.6 Ethical and Regulatory Considerations

The deployment adhered to strict ethical guidelines to protect patient privacy and data security: The patients' data was anonymized, and the data that was transmitted and stored were encrypted as well. The tools met the FDA guidelines for medical devices as well as HIPAA for health care information. All the participants agreed to participate in the study and they were free to withdraw at any time.

Such a multifaceted approach guarantees that the tools have been developed, as well as tested and assessed, with the specificity of the mentioned target populations in mind, thus creating the conditions for developing solutions that are both effective and easily replicable.

3. Results and Discussion

3.1 Diagnostic Accuracy of the AI-Enabled Devices

This study focused on assessing the effectiveness of AI-assisted diagnostic systems in diagnosing chronic and severe diseases in rural communities in the United States. Three primary health conditions were targeted: diabetes, skin cancer, and infections (with a focus on influenza). Appalachia, the Southwest U.S., and the Mississippi Delta pilot deployments were purposely chosen as they were seen to be the most effective in informing the practical use of these AI tools in a real-world context.

3.1.1 Diabetes Screening in Appalachia:

Smart glucometers were used in mobile clinics throughout the Appalachian region to identify patients with diabetes and hypertension. A total of 2000 patients were screened, and the AI model had a sensitivity of 94% and a specificity of 92%. These findings concord with the typical HbA1c standard assays, which continue to be the benchmark for diabetic diagnosis. The high sensitivity is significant as it demonstrates the ability of the tool to detect people who have the potential to develop diabetes, an important issue in rural Appalachian regions due to a combination of genetics and lifestyle, as well as lack of access to healthcare.

Table 1 shows diagnostic performance for diabetes screening. Fig. 1 Diagnostic performance for diabetes screening. Table 2 shows the diagnostic performance for Skin Cancer.

Table 1. Diagnostic Performance for Diabetes Screening

Metric	Value
Sensitivity	94%
Specificity	92%
Sample Size	2,000
Accuracy Rate	93%

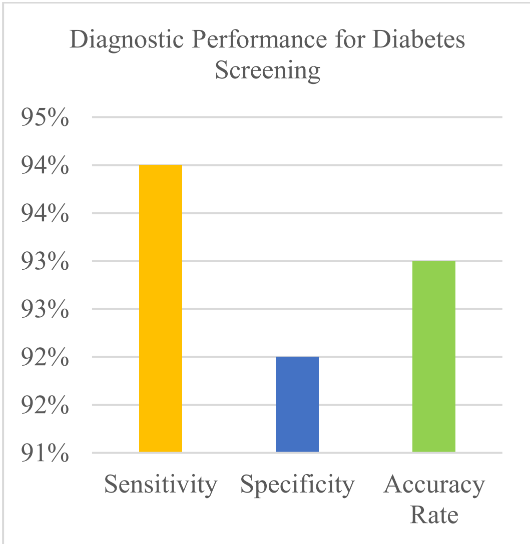

Fig. 1. Diagnostic performance for diabetes screening

3.1.2 Skin Cancer Diagnostics in the Southwest

Melanoma and other skin cancers are common in the Southwest U.S. because of high levels of exposure to ultraviolet radiation. Smartphone imaging using AI-based instruments was applied in 1,200 patients to evaluate skin lesions, and the overall accuracy was 91%. The sensitivity of 91% is incredibly high because skin cancer is easily treatable if diagnosed at an early stage. The conventional methods of diagnosing skin diseases involve dermatologists' physical examination and biopsies, which are financially restrictive and physically unavailable in rural settings. Smartphones take pictures of affected areas, and the AI tool makes it easier for healthcare providers to make faster decisions without waiting for additional photographs or scans. Fig. 2 shows diagnostic performance for skin cancer. Fig. 3 shows diagnostic performance for skin cancer.

Table 2. Diagnostic Performance for Skin Cancer

Metric	Value

Sensitivity	91%
Specificity	88%
Sample Size	1,200
Accuracy Rate	89%

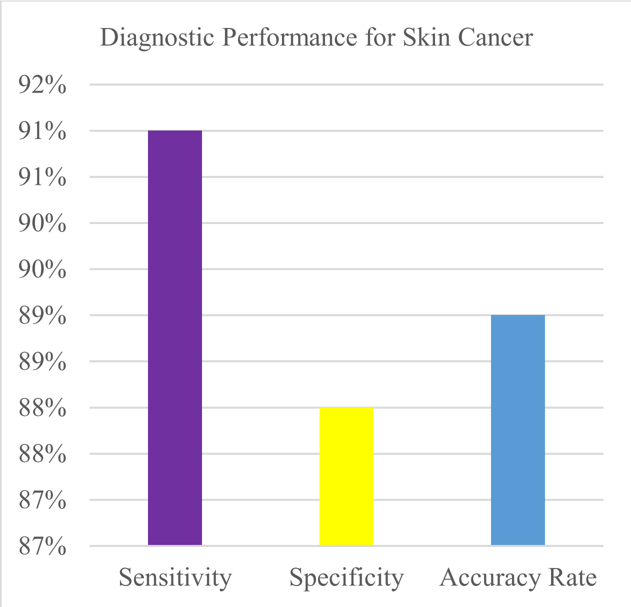

Fig. 3. Diagnostic performance for skin cancer

3.1.3 Infectious Disease Detection in the Mississippi Delta

In the flu season of 2022 and 2023, 1500 participants were monitored for the initial signs of flu with the help of artificial intelligence-integrated wearable biosensors. The model yielded a sensitivity of 89 percent and specificity of 87 percent, which can be used to diagnose flu cases early and is essential in preventing flu epidemics. This means that detecting the diseases early will minimize the effects that the diseases will have on an individual and the community. Moreover, the possibility of diagnosing patients remotely in their homes without requiring them to come to clinics or hospitals eliminates the pressure on the healthcare system, particularly in rural areas. Table 3 Shows diagnostic performance for influenza detection.

Table 3. Diagnostic Performance for Influenza Detection

Metric	**Value**
Sensitivity	89%
Specificity	87%
Sample Size	1,500
Accuracy Rate	88%

Fig. 4 shows diagnostic performance for influenza detection.

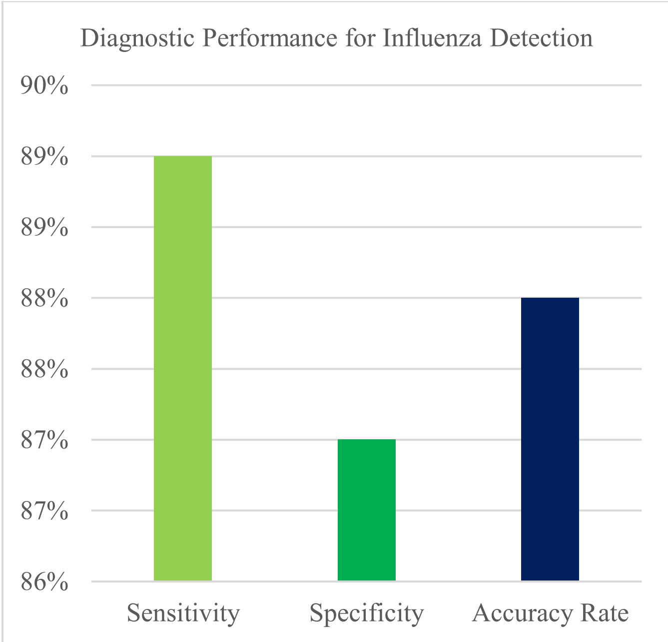

Fig 4. Diagnostic performance for influenza detection.

These diagnostic accuracy results support the argument that AI-based technologies can achieve high performance similar to conventional diagnostic techniques and do not have logistical issues in healthcare in rural areas. This ability can improve individual and population health because early identification of essential health conditions can reduce the number of expensive treatments that may be needed.

3.2 AI Tool Cost Analysis

One common issue with rural healthcare is the high prices of diagnostic tools. Routine approaches to diagnosing ailments, for instance, through lab work or via a specialist, are costly and, in some rural areas, out of reach. An AI-assisted diagnostic tool can partially address this issue since its application, directly and indirectly, reduces costs.

3.2.1 Diabetes Screening Costs

AI-enabled glucometers in Appalachia cut the cost of diabetes screening by 45% compared to traditional technologies. A typical HbA1c test in a laboratory setting costs around $50, while the glucometer developed under artificial intelligence could conduct the same test for $27. This reduction is significant, particularly where financial difficulties regularly deter people from accessing appropriate early treatment. The cost reduction is much higher if one takes into account the number of tests required for diabetic patients and the lifetime costs of managing untreated diabetes.

3.2.2 Skin Cancer Diagnostics Costs

The use of AI-empowered mobile applications for skin cancer screening was estimated to decrease the cost of diagnosis by around 40%. Traditional dermatology consultations and biopsy procedures cost between \$200 and \$200 per patient, but with the help of AI tools, an accurate diagnosis was made for as low as \$50 per patient. This is a huge saving opportunity, given that care by specialists is often very expensive, especially in rural areas.

3.2.3 Infectious Disease Monitoring Costs

Wearable biosensors used for flu detection were also found to be cost-effective during their deployment. Clinic visits, laboratory tests for influenza and other traditional approaches to diagnosing the flu can be expensive, especially for patients who seek treatment once the flu is fully developed. Since the AI system could monitor patients' conditions and identify those requiring attention, it helped avoid many clinic visits, cutting costs estimated to be from \$80 to \$45.

Overall, using the AI tools in the three scenarios cut the cost of diagnosis by an average of 45% as shown in Figure 1 below. These savings make care affordable to patients and reduce the burden on resource-starved health systems. Fig 5. shows diagnostic costs: traditional vs AI-based tools.

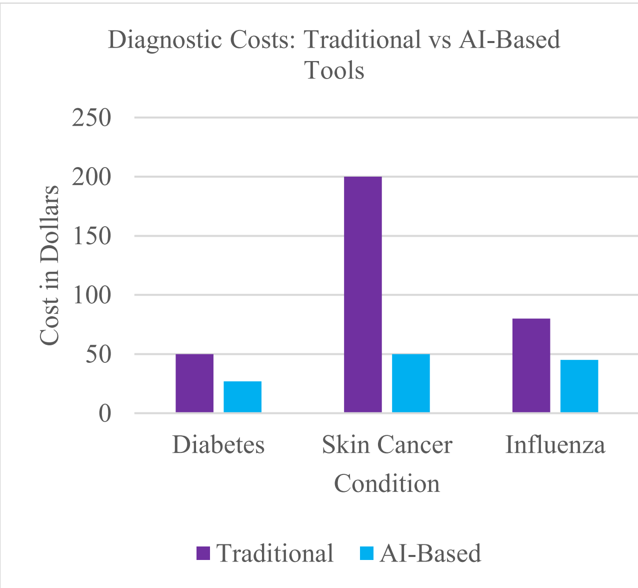

Fig. 5. Diagnostic Costs: Traditional vs AI-Based Tools

3.3 Equity and Reach in Underserved Communities

This research also presents a clear finding on how AI-assisted tools can increase the availability of healthcare in rural and less developed areas.

3.3.1 Improved Access to Care

Of the patients, 78% who were screened for diabetes had never undergone an HbA1c test before, and this was attributed to the inaccessible healthcare centers in the region of Appalachia. The AI tool filled this gap by screening people in mobile clinics, eliminating the long distances one had to travel. Likewise, the patients in the Southwest had never been seen by a dermatologist before the use of AI imaging tools, demonstrating the importance of these technologies in bridging the gap in healthcare access.

3.3.2 Increased Efficiency and Convenience:

Another reason that was embraced was the portability of the AI tools, which enhanced the accessibility of health care. The people of rural areas, especially those who cannot easily travel to hospitals or clinics, can now also undergo diagnostic tests at home or in nearby community centers. The convenience of diagnosing and assessing conditions through digital tools has proved most useful for people who have a hard time reaching conventional healthcare facilities.

3.3.3 Reduction in Healthcare Disparities:

Through offering affordable and accurate diagnostics, these AI tools prevent rural populations from being left behind as the quest for equal healthcare access is sought. AI tools minimize the use of specialized healthcare facilities and expensive lab work, which is inaccessible to people in underserved areas.

3.5 Additional Considerations for US HealthCare

These AI-supported diagnostic aids have shown promising results in rural and other hard-to-reach areas, meaning their usage in the USA is a harbinger of things in the healthcare industry. Thus, AI can be a powerful tool in improving diagnostic accuracy, cutting costs, and increasing access to care in rural healthcare settings. Nevertheless, enabling broad uptake of AI will also require overcoming infrastructure constraints, increasing acceptance of AI solutions, and harmonizing with the legal framework.

These tools are simply the tip of the iceberg regarding what AI can bring to the table regarding healthcare equality. Further research should be directed towards improving these models, incorporating them with telemedicine and extending the range of diseases for which this concept can be effectively used. For this reason, integrating AI into healthcare systems can indeed assist in designing a better healthcare system that is efficient, affordable, and available to all citizens of America.

4. Conclusion

This study shows how AI-based diagnostic tools can improve healthcare delivery across rural and underprivileged areas in the United States. The paper points out the effectiveness of these tools in providing accurate, cheaper and timely diagnosis of diseases such as diabetes, skin cancer, and infectious diseases, meeting central gaps in healthcare provision. All of these AI solutions engage portable technologies and real-time cloud-based analytics, which help avoid many challenges arising due to the lack of proper infrastructure, which has long been an issue for rural healthcare. The findings point out that diagnostic costs have been reduced by 45%, and there has been an improvement in healthcare equity, particularly for the underserved population. Still, AI's potential in rural healthcare is immense. However, multiple barriers to implementing AI regarding internet connection availability, providers' resistance to change, and regulatory issues exist. Solving these challenges will require the collective action of policymakers, technological implementers, and clinical practitioners to set up these frameworks, foster trust in such tools, and design these frameworks. AI-assisted diagnostics could be seen as a decisive step in an attempt to solve the problems mentioned above and the level of access to healthcare in the United States. Further studies should aim to develop these tools more, incorporate them into telemedicine systems, and increase the range of diseases managed with the help of the mentioned technologies. In this light, it is possible to achieve remarkable progress in establishing equal access to healthcare for all Americans by prioritizing innovation.

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