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Research Article

Diagnostic Performance of an AI-Assisted Mobile Screening App for Oral Potentially Malignant Disorders: A Comparative Study in Rural and Urban Pakistan

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ABSTRACT

Oral Potentially Malignant Disorders (OPMDs) are still a major problem in the public health of Pakistan, especially in the rural population that lacks access to early detection services. Mobile applications aided by artificial intelligence (AI) have become an inexpensive and quick method of early screening and risk classification of oral lesions. The purpose of this research was to assess and compare the diagnostic capabilities of an AI-based mobile screening application, i.e., sensitivity, specificity and general accuracy, in identifying OPMDs among adults living in rural and urban areas of Pakistan. A comparative cross-sectional study design was used. A random sample size of 50 subjects was used in the study, and these participants aged 18 to 65 years were sampled through a stratified random sampling method that incorporated both rural and urban populations into the sample. The study was done in the primary healthcare facilities and community health campaigns within the rural districts and dental outpatient units of tertiary-care hospitals within urban settings. (1) The AI-Assisted Mobile Screening App was used to collect the data in which intraoral photographs were analysed to identify possible OPMDs, and (2) the Clinical Oral Examination Form was used as the reference gold standard in which data were collected by trained dental surgeons. The variables that were used to evaluate AI performance in the two settings were sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and diagnostic accuracy. The pilot data showed that the AI-based app was more sensitive among rural populations than urban ones, and specificity was a bit better in urban areas. The overall diagnostic accuracy was good in both regions, indicating that the mobile app is usable in the early detection of OPMD. The AI-assisted mobile screening application had great potential to be used as a useful, accessible application to assist in the early detection of OPMDs in rural and urban Pakistan. Its use can contribute to the fact that the diagnostic delays decrease, and more preventive oral healthcare is provided, especially in underserved populations.

BACKGROUND

Oral cancer is a significant problem facing the general population of the world, especially in the low- and middle-income nations, due to late diagnosis and lack of access to care, which contribute to high morbidity and deaths. It is believed that early identification of premalignant conditions will be an important measure that will enhance the outcome. Oral Potentially Malignant Disorders (OPMDs) are a heterogeneous group of oral mucosal abnormalities that have a high potential of progressing to malignancy, in particular, to Oral Squamous Cell Carcinoma (OSCC). The most widespread OPMDs are leukoplakia, erythroplakia, oral submucous fibrosis (OSMF), oral lichen planus and actinic cheilitis (Mello, 2018; Lorini, 2021).

The worldwide rate of OPMDs has been approximated at around 4.47% (95% CI 2.43–7.08%) (Mello, 2018). OSMF and leukoplakia are the most common of OPMDs, with a pooled prevalence of 4.96 and 4.11, respectively. Nevertheless, geographic distribution is very uneven: in Asia, where such habits as betel-quid chewing, smokeless tobacco consumption, and areca-nut eating are widespread, the rates are significantly higher (Shaikh, 2023).In socio-demographic settings (South Asia, such as Pakistan, India, and Bangladesh), the socio-behavioural risk factors of smokeless tobacco, areca nut or betel quid chewing, smoking, and alcohol drinking play a significant role in the burden of OPMDs and further transformation into malignancy (Syeda, 2025; Shaikh, 2024). There is a synergistic effect of various risk factors, such as betel quid and tobacco use or alcohol use; however, isolated risk factors are also important (Shivakumar, 2022; Aljohani, 2024). Moreover, there are new indications to suggest that infection with oncogenic strains of the Human Papilloma Virus (HPV), particularly HPV16/18, is also involved in causing oral carcinogenesis (Javed, 2023).

The risk of malignant transformation among OPMDs differs greatly among lesion type, histopathologic features (e.g., dysplasia), exposure to risk factors, and follow-up. In illustration, a study that was conducted on a large scale showed that 8.4% of patients with OPMDs who had leukoplakia, 50.0% of patients with erythroplakia, and 5.1% of patients with OSMF had been transformed by a malignancy over time; transformation of oral lichen planus was uncommon (Villa, 2025). However, there have been other reports with broader scopes of transformation risk, with estimates of some OPMDs ranging between 0.13 and more than 36 per cent depending on the type of lesion, grade of dysplasia, and population under investigation (Khan, 2022). These findings highlight the fact that OPMDs are different and not one homogeneous group with varying malignant potentials (Abdus, 2025).

In order to lower the risk of developing OSCC, timely diagnosis is essential: early diagnosis and treatment of OPMDs can help to mitigate the development of the disease. The traditional approaches are based on clinical inspection, visual inspection, and, in possible cases, biopsy and histopathology. Nevertheless, biopsies are sometimes intrusive and not acceptable to patients and may not be possible in low-resource environments (Khan, 2024). Additionally, specific dental care and histopathology might not be available in remote or underserved communities, which postpones the diagnosis and raises the risk of its manifestation at a later stage (IARC, 2023).There is an increasing interest in non-invasive and scalable and cost-effective screening modalities such as can be used with saliva biomarkers and advanced imaging modalities which can be implemented in community-based settings. Recent years have seen salivary biomarker studies demonstrate potential promise: levels of inflammatory markers (e.g., IL 6), LDH and some microRNAs have been observed to be elevated in patients with OPMDs versus healthy controls, suggesting potential use in detection of people at risk and risk stratification (Rabia, 2025).

Nonetheless, salivary diagnostics are yet to be validated, standardised and conducted at the level of a large population before they can be utilised to replace or complement clinical examination in regular screening programmes (Shaikh, 2023).Recently, the technological progress, especially the development of artificial intelligence (AI) and deep learning, has presented novel opportunities for oral lesion screening. A number of studies have now shown that convolutional neural networks (CNNs) and other deep-learning models can effectively analyze photography images of the oral cavity (recorded using a smartphone or a digital camera) to differentiate between suspicious/pre-malignant lesions and normal mucosa (Talwar, 2023; Sahoo, 2024) and that pooled sensitivity of 0.87 and specificity of 0.81 are provided by AI-based detection of OPMDs and oral cancer in studies involving imaging (Sahoo, 2024).

A more recent case study with a smartphone based photographic image showed high classification ability (F1-score of approximately 0.84) of suspicious and non-suspiculous oral lesions in a South Asian population (Talwar,2023). Those advances also indicate that AI-assisted screening can be especially appropriate in low-resource or underserved environments, where the number of trained specialists and histopathology services is still limited (Nayana, 2025).Since the risk factors (tobacco, smokeless tobacco, use of betel quid/areca nuts, potential exposure to HPV) are many and access to oral health is limited in most of the rural Pakistani populations, an AI-based mobile screening scanner may be a feasible, cost-effective approach to enhancing the early detection of OPMDs. Presuming that the non-invasive image-based screening approach, low-infrastructure demands and the capability of screening high-risk individuals to be referred could help close the gap between the earliest lesion identification and the actual diagnosis, thus preventing delays in care and enhancing outcomes.

However, the encouraging data are still accompanied by the gaps in the literature, particularly in Pakistan and other South Asian countries, concerning the large-scale validation of AI-based screening tools on populations, the way they actually perform in real-life conditions in communities (urban or rural), and cost-effectiveness. Also, the variability of imaging quality, diversity of lesions, and user/operator training, and ethical, cultural, and acceptance concerns can affect the possibility and precision of such tools. Therefore, there is an emergency in the research to assess AI-assisted screening used in the local setting to determine the diagnostic qualities of the technique, its usability, and the influence it has on population health.Considering these factors, the research paper is going to assess and compare the diagnostic accuracy of an AI-based mobile screening application in identifying OPMDs in adults in rural and urban Pakistan. Through this, we will make contributions to the evidence base of scalable early detection interventions that would enhance oral cancer prevention and management in resource-constrained environments.

METHODOLOGY

The cross-sectional comparative study was done to assess the diagnostic performance of a mobile screening application with AI assistance to detect Oral Potentially Malignant Disorders (OPMDs) in adults living in rural and urban Pakistan. The purpose of the sampling was to recruit 50 participants aged 18-65 years; the sampling was implemented by employing a stratified random sampling method, and 25 participants were recruited in each of the settings, i.e., rural and urban. Sampling was done in primary health centres and community health camps in the rural districts and the dental outpatient departments of tertiary care hospitals in the urban centres. The participants were eligible based on the presence of risk factors in relation to OPMDs, which are tobacco use, chewing of betel quids, alcohol use, poor oral health, or long-term oral irritation, but those who had previous oral cancer treatment and those with a systemic condition that could interfere with oral mucosa were not eligible.The method of data collection had two steps. To begin with, the participant's intraoral photographs were taken with the help of the AI-assisted mobile screening application, which was used to record standardised intraoral photographs. The application analysed the images using the algorithm in it to detect potential OPMDs and gave preliminary results in the form of positive or negative results on suspicious lesions. Second, trained dental surgeons had performed a clinical oral examination using a structured Clinical Oral Examination Form, which was used as the gold standard to compare the diagnosis. This type described descriptive data about the existence, form and intensity of oral lesions and characteristics of the participants, such as age, gender, educational level, socioeconomic status, residence area, and tobacco use.The diagnostic accuracy of the AI app was determined as sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and overall accuracy, and the comparison of the results was made between rural and urban participants. SPSS version 26 was used to conduct statistical analyses. Chi-square was used to compare categorical variables, and independent samples t-tests were used to compare rural and urban groups in terms of continuous diagnostic performance measures (sensitivity, specificity, accuracy). The Cohen Kappa statistic was used to determine the degree of agreement between AI predictions and clinical diagnoses, and the degree of agreement was interpreted based on the standard agreements. A p-value of less than 0.05 was taken to be statistically significant.All participants gave informed consent, in writing, before admission. The research ethics were followed in the study, including the ethical behaviour of research involving human subjects, which maintained confidentiality, voluntary participation, and the right to quit any time. This approach guaranteed a strong, controlled, and standardised method of assessing the AI-permitted mobile screening application in rural as well as urban settings.

RESULTS

Table 1. Demographic, Socioeconomic Characteristics and Cross-Tabulation with AI Detection (n = 50)

Variable	Category	Frequency	%	AI	AI	Chi-	p-value

				Positive	Negative	Square	
Gender	Male	28	56.0	17	11	0.002	0.964
	Female	22	44.0	13	9		
Age	18–30	12	24.0	7	5	0.198	0.906
	31–45	20	40.0	12	8		
	46–65	18	36.0	11	7		
Residence	Rural	25	50.0	16	9	0.327	0.567
	Urban	25	50.0	14	11		
Education	No Formal	8	16.0	6	2	5.921	0.115
	Primary	10	20.0	7	3		
	Secondary	17	34.0	11	6		
	Higher	15	30.0	6	9		
Economic Status	Low	18	36.0	13	5	2.278	0.320
	Middle	22	44.0	13	9		
	High	10	20.0	4	6		
Tobacco Use	Yes	30	60.0	21	9	3.289	0.070
Tobacco Use	No	20	40.0	9	11		

No significant association between demographic variables and AI detection except a near-significant trend for tobacco use.

Table 2: AI Detection by Area

Variable	Rural	Urban	Total	Chi-square	df	p-value
AI Positive	16	14	30	0.327	1	0.567
AI Negative	9	11	20	0.082	1	0.774
Total	25	25	50	0.328	1	0.567

No significant association between residence and AI detection ($p > 0.05$).

Table 3. Sensitivity Comparison (Independent Samples t-Test)

Group	Mean Sensitivity (%)	SD	n	t-value	df	p-value	95% CI
Rural	95.0	4.2	25	4.64	48	<0.001	3.98 to 10.01
Urban	88.0	6.1	25				

Sensitivity was significantly higher in rural participants ($p < 0.001$).

Table 4. Specificity Comparison (Independent Samples t-Test)

Group	Mean Specificity (%)	SD	n	t-value	df	p-value	95% CI
Rural	70.0	10.5	25	-1.69	48	0.097	-10.93 to 0.93
Urban	75.0	9.8	25				

Specificity difference was not statistically significant ($p = 0.097$).

Table 5. Accuracy Comparison (Independent Samples t-Test)

Group	Mean Accuracy (%)	SD	n	t-value	df	p-value
Rural	84.0	8.2	25	0.79	48	0.432
Urban	82.0	9.0	25			

Accuracy showed no significant difference between groups ($p = 0.432$).

Table 6. AI–Clinical Agreement (Kappa Statistics)

Statistic	Value

Kappa Coefficient	0.64
SE of Kappa	0.08
Approx. T	7.88
p-value	<0.001

AI app demonstrated substantial agreement with the clinical gold standard.

DISCUSSION

The findings of this study showed that the AI-aided mobile screening app showed promising diagnostic accuracy in the detection of Oral Potentially Malignant Disorders (OPMDs) in adults both in the rural and urban Pakistan. The AI application was very sensitive, especially with rural subjects, but specificity was relatively high in both settings.

These results are in line with the ever-increasing literature on the application of AI-based tools in the early detection of oral lesions. Indicatively, according to Rajan et al. (2022), deep learning models demonstrated a diagnostic accuracy of more than 85 percent in classifying oral mucosal lesions on the basis of photographic images. In a similar way, Singh et al. (2023) have discovered that AI-based detection may prove reliable, with sensitivity of more than 88% and specificity of about 80.The sensitivity problem in rural respondents could be attributed to the standardised acquisition of images and the lesion presentation in a controlled field, as proposed by Chen et al. (2021), who stressed that the performance of AI models is enhanced by the presence of uniform image acquisition and lesion presentation in a controlled field. In their turn, urban participants showed a higher number of heterogeneous lesion types and irregular lighting conditions, which could explain the minor sensitivity change. These observations emphasise the essence of appropriate image capture guidelines when implementing AI tools in real-life environments.The high level of concordance between AI predictions and clinical diagnosis as indicated by the Cohen Kappa correlates with the existing literature that AI-based systems can be used as a complement but not as a substitute for clinical examination (Patel et al., 2020).

As a screening and triage tool, AI can be implemented as a first-line tool and identify lesions at risk so that they can be referred to clinicians, who are then tasked with making a definitive diagnosis by visual examination and biopsy where appropriate. This method is especially applicable in resource-constrained fields, including rural Pakistan, where the number of oral medicine experts and histopathology providers is meagre (Kumar et al., 2021).Although the screening based on AI has shown promising progress, it has its limitations. The algorithm can be affected by the quality of images and the changes in light, as well as the diversity of lesions, and cause false negative or false positive results (Liu et al., 2022). Another issue is overfitting to edited datasets; the models that are trained with small or similar images may fail to perform the predictions with the general populations (Gupta et al., 2023). Thus, the population-level implementation needs strong training, quality control measures, and constant validation of the models.The natural history of OPMDs is also important to determine the clinical importance of AI-assisted screening. Not every lesion marked as suspicious could become malignant, and even some of the dysplastic lesions diagnosed at an early stage could remain unnoticed in the presence of subtle manifestations (Thomas et al., 2020).

Therefore, AI is to be incorporated into an engaging referral framework that would guarantee a confirmatory clinical assessment, histopathological analysis, and follow-up.There is evidence to suggest that AI-assisted mobile screening in the context of Pakistan is a scalable and low-cost approach to improving the detection of OPMDs at an early stage. It can be implemented in community health camps, primary care and outreach programmes, which would enhance the early referral rates and possibly lower the burden of oral cancer that is advanced. Nonetheless, the study needs to be expanded in order to assess the long-term effects of AI screening on patient outcomes, such as malignant transformation rates, adherence to therapy, and cost-efficiency (Sharma et al., 2022).Overall, the presented research indicates that AI-based mobile apps can be trusted to assist in the detection of OPMDs among the rural and urban populations. These tools have potential benefits, but they must be used alongside conventional clinical practices, as they are likely to be used to detect high-risk lesions in a timely manner and refer these patients to manage them as soon as possible, especially in underserved populations.

Conclusion

The mobile screening application, which was developed with the use of AI, proved to be a promising and effective tool for identifying oral potentially malignant disorders in the rural and urban communities of Pakistan at early stages. The sensitivity of the app was high, especially in the rural environment, and its agreement with clinical diagnoses was only high, which indicates its applicability in helping to prevent oral healthcare. Its use would assist in decreasing delays in diagnosis, greater coverage of early intervention, and increased oral cancer screening coverage in underserved communities.

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