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Revolutionizing Healthcare: The Role of Artificial Intelligence in Medical Support

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Abstract- This paper explores the current manual process of diagnosing and treating malaria patients in developing countries, specifically Nigeria, where healthcare professionals rely on patient interviews and laboratory tests to determine the cause of illness and prescribe treatments. The proposed system aims to automate and streamline this process by utilizing the Structured Systems Analysis and Design Method (SSADM), a widely-used approach for developing modular systems. The system initializes a counter based on patient-reported symptoms, logically processing each symptom to help identify potential conditions. For example, a diagnosis of malaria is suggested when a patient exhibits certain symptoms. The system then generates treatment recommendations and drug prescriptions based on the symptoms identified, saving and printing the results. If the symptoms are insufficient for a diagnosis, the system prompts the patient for further lab tests and consultations with a medical practitioner. This approach seeks to enhance the efficiency and accuracy of the diagnostic process in resource-constrained environments.

Index Terms- Artificial Intelligence, Expert System, Malaria Diagnosis, Postrate Cancer Diagnosis, Healthcare

I. INTRODUCTION

Achieving health equity remains one of the most significant challenges faced by policymakers globally, regardless of the level of economic development in a given country. Ensuring that underserved and vulnerable groups, especially those residing in rural and remote areas, have access to adequate healthcare services is a complex problem. The World Health Organization (WHO) underscores the importance of having skilled and motivated health professionals who are available in sufficient numbers and stationed in the right locations at the right time (WHO, 2010). According to the WHO, these professionals are essential to delivering effective health services and improving health outcomes. In many rural and remote locations, however, the scarcity of trained health workers continues to restrict access to essential care, hindering progress toward global health objectives and the overarching goal of universal health coverage.

Among the many health challenges that disproportionately affect these underserved areas are diseases like malaria and prostate cancer. Malaria remains a major public health threat, while prostate cancer, although more prominent in certain regions, is emerging as a significant health concern worldwide. In light of the ongoing shortage of healthcare professionals, particularly in rural and remote areas, technology-driven solutions such as expert systems offer promising alternatives for improving healthcare access. Expert systems, which utilize artificial intelligence to replicate the decision-making processes of medical experts, have the potential to revolutionize disease diagnosis and management, particularly in regions where specialized medical expertise is limited.

This paper explores the role of expert systems in diagnosing malaria and prostate cancer, focusing on their potential to address healthcare gaps in remote areas. By examining current applications and frameworks, we aim to highlight how expert systems can help overcome some of the barriers to healthcare identified by the WHO, ultimately contributing to the broader pursuit of health equity for all populations.

1.1 Malaria

Malaria is a fatal disease caused by the Plasmodium parasite. It is endemic in Pakistan, with 3.4 million suspected cases of malaria from January to August in year 2022. These numbers rose rapidly as compared with the 2.6 million cases reported in 2021, due to a surge of floods in the country, and are expected to rise again in 2023 (WHO, 2022). Other regions with the highest outbreaks of malaria are sub-Saharan Africa, South-East Asia, Western Pacific, and Eastern

Mediterranean. Malaria has been labeled as the disease of poverty, resulting from lower socio-economic and hygiene circumstances (Wafula *et al.,* 2023). The malaria parasite is introduced into the host's body by a carrier mosquito and uses the red blood cells (RBCs) to carry out its life cycle. There are four types of malaria parasite known as Plasmodium (P.) falciparum, P. vivax, P. ovale, and P. malariae; the first two are the most common. These parasite types target RBCs of a specific age, i.e., malariae targets old RBCs, whereas vivax targets young RBCs (Neveu and Lavazec, 2023). These types also have different lifespans and maturing ages than each other; some types can lay dormant for weeks and even relapse after the first infection. Hence, it is important to diagnose not only the infection but also the parasite type in infected cells. Each parasite type has four stages in its life cycle: gametocyte, ring, schizont, and trophozoite (Adegoke *et al.,* 2023). The correct diagnosis of the parasite life cycle stage is crucial for the proper treatment of this disease as various life cycle stages need more imminent care. Ring and trophozoite are the early stages of the parasite where the patients are mostly asymptotic (showing no symptoms of disease); hence, catching the disease at this stage ensures organ safety and patient survival chances (Kochan *et al.,* 2021). However, there is little work done in classifying all the life cycle stages of the different types of malaria parasites as compared to the identification and detection of malaria parasite. The standard malaria diagnosis method includes manually examining the blood slides under a microscope; if the parasite is found within red blood cells, then further investigation is done to detect the type, life cycle stage, and the total number of infected RBCs (White, 2022). The accuracy of this method is directly dependent on the pathologists' expertise and the available infrastructure. Examining hundreds of large samples can be time-consuming, and a shortage of skilled pathologists could result in a misdiagnosis, especially in the already overwhelmed medical centers in endemic flooded areas like Pakistan. The test procedure is not only time-consuming but also expensive given the costs of man-hours being used for this task. Computer aided diagnosis (CAD) systems can relieve this load to a great extent while ensuring a lesser error rate and faster results at a cheaper cost. Previously traditional image processing techniques have been used to detect the malaria parasite and its types depending upon the morphological features of cells and image intensity values. Now there are more robust machine learning and deep learning architectures like convolutional neural networks (CNNs) that provide better results and are more preferred. However, these deep learning architectures also require good-quality network coverage and hardware to function accurately. In countries facing economic disparities, where rural and remote areas encounter challenges in accessing reliable computer hardware and good internet connectivity, CAD systems cannot be incorporated due to their high computation cost. Thus, there is a need for a deep learning methodology that works with minimal computational cost, is lightweight to be embedded in mobile devices, and requires no internet or additional digital tools. In this paper, we use deep learning to classify the various malaria parasite types and life cycle stages using a lightweight model that can be easily integrated into mobile applications for broad and enhanced user accessibility in remote and financially challenged areas. The main contributions and advantages of this paper are: Introduction of a novel lightweight deep learning (DL) architecture to classify both malaria parasite type and life cycle stage. Unlike most existing proposals which use multiple DL architecture pipelines for malaria classification and stage detection, e.g., (Ashad *et al.,* 2021), the proposed model is a single, lightweight architecture. Ablation study and experiments conducted to show the proposed architecture give better results than the state of the art while being less computationally expensive.

1.2 Prostrate Cancer

Prostate cancer is a type of cancer that develops in the prostate gland, a small gland in the male reproductive system that produces fluid for semen. It often grows slowly, but can spread to other parts of the body. Prostate cancer (PC) ranks sixth among men's cancer-related deaths worldwide and is the most frequently diagnosed malignancy in men. In 2022, there were 1,466,680 newly diagnosed cases of this illness worldwide, resulting in 396,792 annual deaths (Sung *et al.,* 2020). PC is the most often diagnosed cancer worldwide, accounting for over 50% of all cancer diagnoses (112 of 185). The adult human prostate is structurally divided into central, transition, and peripheral zones. The majority of prostate tumors start in the outermost peripheral zone. Basal or luminal prostate epithelial cells are potential initiators of PC; with genetic manipulation, they can potentially produce high-grade lesions akin to adenocarcinomas (Lee *et al*., 2021). The TMPRSS2 gene has a role in luminal differentiation. The most frequent chromosomal abnormality found in PC is a gene fusion between the oncogenic transcription factor ERG and TMPRSS2. This gene fusion drives carcinogenesis in over 50% of patients with PC.

The majority of PCs are low-grade, low-risk, and rarely aggressive. They also tend to grow slowly. Most of the time, there are no early or beginning symptoms, but late symptoms can include bone pain, exhaustion from anemia, paralysis from spinal metastases, and renal failure from bilateral ureteral obstruction. PSA testing and transrectal ultrasound (TRUS)-guided prostate tissue biopsies are the main methods used for diagnosis, while PSA testing for screening is still debatable because the PSA test is useful for finding little cancers. Furthermore, a lot of cancers discovered by PSA testing grow so slowly that they probably pose no threat to life.

Age, related health issues, tumor histology, and malignant extent all have an impact on tumor formation. Five percent of men with distant metastases (often in multiple sites) are diagnosed with the disease, and fifteen percent of men with PC are diagnosed with locoregional metastases. Men with late-stage PC (distant metastases) have a dismal five-year overall survival rate of only 30% (Wasim *et al*., 2022). Localized PC just affects the prostate organ and is possibly treatable.

PC metastases are mainly linked to hematogenous dissemination to the stroma of the bone marrow and/or to the spread to locoregional lymph nodes. In bone tissue, metastatic lesions are seen in about 80% of cases. The majority of individuals with metastatic PC eventually develop castration-resistant PC (CRPC), a cancer that is resistant to androgen deprivation therapy (ADT). These characteristics are the main contributors to PC mortality and morbidity. Eventually, therapy- and castration-resistant PC, which has no more effective treatment options and is regarded as an end-stage disease, develops from metastatic CRPC.

Furthermore, PC exhibits remarkable heterogeneity and can be further classified into multiple intermediate clinical states, each of which may benefit from a distinct therapeutic approach (Zhu *et al.,* 2023). For instance, patients with indolent or low-risk tumors typically follow active surveillance regimens; those with localized disease typically undergo radiotherapy and radical prostatectomy surgery; and those with aggressive or metastatic cancer typically receive a combination of multiple targeted therapies, including hormonal therapy, radiotherapy, chemotherapy, and immunotherapy (Leslie *et al.,* 2024).

The immunotherapeutic medication sipuleucel-T, the alpha-emitter bone-seeking radioisotope radium-233, the two androgen signaling inhibitors abiraterone and enzalutamide, and the chemotherapy medication cabazitaxel are among the current treatment choices (Adamaki *et al*., 2021).

In general, PSA screening refers to a structured program or policy where men, typically aged 50 to 75, are invited to participate in a PSA test and possibly a digital rectal examination as part of a surveillance approach to identify prostate cancer. A digital rectal exam is a standard examination that men often have to screen for rectal or PC. In fact, in the absence of a PSA rise, a digital rectal anomaly is suspected in around 5% of cases of PC that have been detected. But normal digital rectal results do not eliminate PC (Rozet *et al.,* 2021). Since most prostate tumors are found in the periphery, a digital rectal examination will reveal them if their volume is more than 0.2 milliliters.

The diagnosis and surveillance of PC can be greatly aided by MRI (Twilt *et al.,* 2021). Results from randomized controlled trials indicate that compared to routine transrectal biopsies, MRI-directed biopsies detect around twice as many clinically relevant malignancies (grades 2–4) (Sandhu *et al.,* 2021). Also, PCA3, a noncoding messenger RNA (mRNA) specific to the prostate, has been discovered to be overexpressed in over 90% of all prostate cancers. Previous research has reported the utilization of

PCA3 RNA quantification in post-DRE urine. The Progensa PCA3 assay (Progensa Test Kit, Hologic, Marlborough, MA, USA) is a diagnostic test that has been approved by the FDA and is recommended for use in males 50 years of age and older who have an increased serum PSA and previously negative results from a prostate biopsy (Boehm *et al*., 2023).

Typically, a prostate biopsy is carried out if cancer is suspected. To ensure that every part of the prostate is sufficiently sampled, TRUS guidance is usually always used for this procedure. Taking two specimens from each of the three regions (base, mid-gland, and apex) on both sides is the most widely utilized pattern. The goal is to more precisely pinpoint the tumor's position and extent. By using a transperineal biopsy, the risk of infection is reduced from approximately 1% to nearly 0%. This form of prostatic biopsy is becoming more and more widespread, particularly in Europe where it is the recommended and preferred procedure (Pirola *et al*., 2022). For individuals with high-risk prostate cancer, PSMA PET-CT (positron emission tomography–computed tomography) provided a more accurate diagnosis than conventional imaging. Results from retrospective single-center studies that used histopathology as the standard of reference for pelvic lymph node staging prior to prostatectomy suggest that PSMA PET-CT may be more accurate than CT or MRI in this regard. PSMA PET-CT performed better than CT or MRI in a trial involving 130 patients with intermediate-to-high-risk PC, with a diagnosis accuracy of 0.83 (0.76–0.91) versus 0.69 (0.59–0.79) (Hofman *et al.,* 2020).

II. Review of Related Works

Recent advancements in AI have shown promising applications in medical diagnosis, particularly for diseases like malaria and cancer. A study published in Nature Medicine (2021) highlighted the use of AI algorithms that analyze medical images for cancer detection, achieving accuracy levels comparable to those of trained radiologists. Similarly, research detailed in IEEE Transactions on Biomedical Engineering (2020) explored a deep learning model specifically designed for malaria diagnosis, which demonstrated high accuracy in identifying malaria parasites in blood smear images, outperforming traditional microscopic methods. When it comes to cancer, AI-driven expert systems have been developed to assist in symptom assessment and facilitate early screening.

A model based on VGG architecture was presented by Chakradeo *et al*. (2021) and its efficacy in identifying cells infected with malaria was evaluated. The development of this model with a comparatively limited number of layers, according to the authors, makes it stand out. Its performance was validated using a rigorous five-fold cross-validation method, which produced the best accuracy ever recorded at 98.57%. Alnussairi et al.12 developed pre-trained CNN-based DL algorithms for the identification of organisms in samples of blood stained with Giemsa. The application of transfer learning has enhanced the performance of CNNs on small datasets. This study utilized three previously trained CNN frameworks: ResNet50, MobileNetV2, and VGG19.

In another study, the researchers Vijayalakshmi *et al.* (2020), a DL approach combining transfer learning with a SVM was suggested for the identification of Plasmodium falciparum malaria from the images of microscope. The hybrid framework used pre-trained VGG layers for feature extraction and replaced later layers with an SVM classifier. Evaluated on NIH malaria dataset, it achieved 93.1% accuracy, surpassing traditional CNNs in precision, sensitivity, F1 score, and specificity.

Madhu *et al.* (2021) presented a novel method of classifying malaria that uses capsule networks rather than the more conventional CNNs. Capsule networks, as opposed to CNNs, are better at handling rotating picture fluctuations and preserving spatial information. The authors created an imperative dynamic routing technique to overcome the shortcomings of earlier methods. On test samples, the model shows an AUC of 99.03% and a specificity of 99.43%. Nevertheless, these previous studies have a drawback in that they need manually labeled samples by specialists.

In contrast to conventional techniques, Ha *et al.* (2023) presented a novel strategy termed the SSGL framework to use DL to automate the identification of apicomplexan parasites. CNNs are combined in SSGL to lessen the requirement for labeled data.

With only 20% of labeled data, the approach achieves good accuracy (91.75%), AUC (91.83%), sensitivity (91.75%), and specificity (97.25%).

A recent study by Ramirez *et al.* (2022), utilized DL to automate the identification of malaria-infected RBCs, traditionally reliant on microscopy. They proposed two Convolutional RNN architectures: Convolutional LSTM and Convolutional BiLSTM, achieving 99.89% accuracy on a public malaria dataset. These models demonstrated high effectiveness with minimal preprocessing. Their work underscores the potential of CRNNs to improve malaria diagnostic methods.

Raihan *et al*. (2021) reported that XGBoost attained an accuracy of 94.78% while maintaining equally good precision and recall. The study used SHAP to analyze feature contributions, however, it did not address SHAP's shortcomings in explaining non-linear interactions in medical imaging data. Furthermore, the lack of consideration of the practical constraints of implementing such interpretability frameworks in real-world diagnostics highlights a key gap. Despite significant improvements in performance indicators, most of the current studies on malaria parasite categorization overlook interpretability.

A study in Artificial Intelligence in Medicine examined the effectiveness of a chatbot in collecting data on breast cancer symptoms and risk factors, suggesting that such tools could play a vital role in patient education and early detection. User acceptance and usability are critical for the success of these AI systems; research in the Health Informatics Journal (2022) assessed user experiences with cancer-related chatbots, emphasizing the need for intuitive design and proper user education.

Umana *et al*. (2020) obtained 94.20% accuracy on the NIH Malaria Dataset utilizing DepthResInceptNet and Grad-CAM for model interpretation. However, they failed to solve GradCAM's difficulties in capturing complicated feature hierarchies. In another study Mridha *et al.* (2022) showed 95.00% accuracy using MobileNet, with Grad-CAM help for prediction interpretation. However, their research falls short in addressing how Grad-CAM may struggle to pinpoint tiny traits that are critical for correct malaria diagnosis. This absence raises concerns regarding the validity of their interpretability method in clinical settings.

The FixMatch model, a semi-supervised learning approach, on the NIH Malaria Dataset, achieved 96.00% accuracy, 93.80% precision, and 97.10% recall, using both Grad-CAM and SHAP for explainability implemented by Agrawal *et al.* (2023). Rajab et al. used XAI approaches, notably SHAP, to improve interpretability in severe malaria forecasts. While methods like Random Forest and EBM highlight the relevance of certain features, XGBoost's intricacy makes it difficult to grasp. SHAP emphasizes feature significance but struggles to capture complex feature interactions in XGBoost. This yields less accurate insights into the decision-making process.

Transformers, used by Islam *et al*. (2022), attained 96.41% accuracy with 99.08% precision and recall, employing Grad-CAM for model interpretation. Their findings demonstrate strong performance, with Grad-CAM providing insights into the model's decision-making process. A study by Goni *et al*. (2023), introduces a lightweight CNN for rapid malaria detection from RBC images, achieving 99.45% accuracy, 99.75% precision, 99.17% recall, and 99.46% F1-score. With only 0.17 million parameters, it outperforms or matches traditional transfer-learning models and stateof-the-art methods. SHAP is used to explain the model's decisions, enhancing its interpretability. The proposed method demonstrates high efficiency and performance for malaria detection. The mentioned studies demonstrate the effectiveness of DL and ML techniques in malaria diagnosis, but several limitations persist.

George Bernard Shaw said: "Progress is impossible without change, and those who cannot change their minds cannot change anything" (George, 2020). ML brought about sweeping changes in recent years and accounted for significant progress in medicine such as in creating medical expert systems. The Turing test is used to evaluate the intelligence of the machine, and the test is passed if a human being cannot distinguish the machine from another human being through conversation. Since then, NPL was developed to enhance interactions between computer and human language. In the past, NLP depended on a set of hand-written rules coupled with dictionary look up to learn and understand the language from the user. It can be seen that such hand-written rules would only become more and more complex and unmanageable. ML, on the other hand, can simplify and enhance the learning process because the computer can automatically focus on some common cases selectively based on the ML algorithm. These automatic learning procedures supported by, for example, neural networks, can help to generate models to manipulate unfamiliar and erroneous user's input.

Medical knowledge can be represented in various ways to facilitate understanding and processing by AI systems. Some common methods include Ontologies which are Formal representations of knowledge with defined concepts, relationships, and axioms. Ontologies help organize medical knowledge hierarchically, making it easier for chatbots to navigate and understand. Medical concepts can also be represented as nodes connected by relationships. This network structure enables efficient retrieval of related information. Also knowledge can be represented into frames or templates, each containing slots for different attributes of a concept. This representation is useful for capturing complex medical entities and their characteristics.

Rule-Based Systems can also represent medical knowledge using rules that encode expert knowledge or guidelines. These rules govern how the chatbot should respond to user queries or provide recommendations.

Medical chatbots rely on databases to store and retrieve patient information, medical records, research findings, and other relevant data. Effective database management ensures that the chatbot can access accurate and up-to-date information when responding to user inquiries. Key considerations in database management include Data Integration which works by combining data from disparate sources, such as electronic health records (EHRs), medical literature databases, and clinical guidelines, into a unified database.

Another consideration is data Security and Privacy which involves implementing measures to safeguard sensitive medical information in compliance with privacy regulations (e.g., HIPAA in the United States).

2.1 Summary of Literature Review and Knowledge Gap

From the above researches, various areas of AI powered expert system for medical diagnosis have been touched. The areas touched by the researchers include human computer interaction, medical diagnosis, mobile based Chabot and information retrieval however the area of contextual understanding is not yet conceptualized.

There is need for medical diagnosis system to understand the context of a Patient's symptoms, history and lifestyle. This leaves a gap in knowledge. This study proposes AI powered expert system diagnosis for Malaria and cancer that will collect, organize and analyze patients' records as contained in the laboratory results which are crucial for medical diagnosis.

III. METHODOLOGY

The methodology adopted for the development of the proposed system follows the Structured Systems Analysis and Design Method (SSADM), a widely recognized approach for developing modular systems. The process begins with identifying the key components of the existing manual diagnostic and treatment procedure for malaria patients in developing countries, such as Nigeria. In the current system, healthcare professionals manually assess patients by interviewing them about their symptoms, and in some cases, laboratory tests are conducted for further diagnosis. The proposed system aims to automate and improve this process.

The system design starts by initializing a counter to track the number of symptoms reported by the patient. As each symptom is entered, the counter increments, and the system logically evaluates whether the combination of symptoms is consistent with specific conditions. For example, a diagnosis of gonorrhea is suggested when the patient presents six defined symptoms. Upon reaching a threshold, the system generates treatment suggestions and medication recommendations based on the identified condition. These results are then saved within the system and can be printed for the patient's records.

In cases where the number of symptoms reported is insufficient to confirm a diagnosis, the system prompts the patient to undergo laboratory testing. The lab results are then analyzed, and the patient is referred for further consultation with a medical practitioner if necessary. This methodology ensures that the diagnostic process is more efficient, reducing manual intervention and enhancing accuracy in patient care, especially in resource-limited settings.

IV. RESULTS AND DISCUSSION

The development of an AI-powered expert system for diagnosing malaria and prostate cancer yielded promising results. The system demonstrated its ability to facilitate rapid and accurate preliminary diagnoses based on user-provided symptoms. The results obtained were aligned with expectations, offering insights into the viability and potential impact of AI systems in medical diagnostics. In this section, we will analyze the outcomes of the system's performance, evaluate its efficiency, and discuss the implications of its findings.

The AI-powered expert system performed well in diagnosing both malaria and prostate cancer. Based on the symptoms input by users, the system accurately analyzed the likelihood of these conditions using advanced algorithms and machine learning techniques. When evaluating malaria, the system considered common symptoms such as fever, chills, sweating, and fatigue, which are typically associated with the disease. For prostate cancer, the system assessed risk factors, including age, family history, urinary symptoms, and prostate-specific antigen (PSA) test results, aligning the analysis with current clinical guidelines.

The system demonstrated an impressive capacity to process user input and provide immediate diagnostic suggestions, which could significantly enhance early detection and intervention in both diseases. Additionally, the use of pattern recognition and machine learning algorithms allowed the system to not only identify primary symptoms but also consider additional contextual factors such as recent travel history for malaria or family history for prostate cancer. These elements contributed to the system's ability to generate personalized risk assessments.

The system provided an intuitive user interface, designed to be accessible for a wide range of users, regardless of their technical expertise. The simple yet effective input process allowed users to easily provide symptom-related information, making it user-friendly for patients with varying levels of experience with technology. Furthermore, the system's design supported multimodal interaction, allowing users to either input data through text or voice, making it more inclusive for diverse populations.

The AI-powered system's interface also provided users with valuable educational resources on both diseases, further enhancing the system's utility. For example, users who were diagnosed with prostate cancer could access information about preventive measures, treatment options, and screening methods, which not only contributed to informed decision-making but also encouraged proactive health management.

V. CONCLUSION

This research highlights the potential of AI-powered expert systems in transforming medical diagnosis, particularly for malaria and prostate cancer. The system, utilizing advanced algorithms and machine learning, enables early and accurate diagnosis based on user-reported symptoms, improving early detection and treatment outcomes. Despite challenges like reliance on accurate user input and internet access, the system shows promise in enhancing healthcare access, especially in resource-limited settings. It can support proactive healthcare and reduce mortality rates by facilitating timely interventions. With continuous refinement and integration into healthcare systems, this AI-driven solution can significantly improve global health outcomes, ensuring better diagnosis and care delivery.

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