Literature Review

1. Introduction

The ability to access healthcare facililtes and providing the necessary care to those who need it is a fundamental humane right that all people should have. In Sudan, there are barriers that prevent acess to this fundamental right especially in conflict-affected areas where infrastructure is usually destroyed and medical supplies are scarce. Socioeconomic inequities like poverty and unemployment exacerbate the problem, along with environmental factors such as flooding that impede access to health services among vulnerable populations.

Traditional disease surveillance and outbreak prediction are usually limited by a lack of data and resources. ML offers much in its potential to drive data-informed decisions, even in resource-poor settings. Machine learning-based methods may help improve the timeliness of epidemic outbreak predictions, allow for more efficient use of resources, and enhance health care. Nevertheless, data challenges, algorithmic biases, and limited resources need to be addressed if the full potential is to be realized in places like Sudan. Purpose of the Review

This review aims to discuss the convergence of healthcare access, disease epidemiology, and machine learning applications in Sudan. By identifying challenges, analyzing disease trends, and assessing ML-driven methods, this study will try to provide practical insights for improving healthcare services and outcomes in Sudan.

2. Healthcare Accessibility:

2.1. Challenges in conflict-affected areas.

The fighting in Sudan has been unending, right through the capital and other parts of the country, hence extremely curtailing humanitarian access, with the general situation in Sudan continuing to deteriorate. These have been very destructive for health infrastructures, hence drastically affecting the delivery of essential services. Numerous hospitals and clinics have been either completely destroyed or rendered inoperable due to bombings, looting, and occupation by armed groups. Consequently, millions of individuals are left without access to medical care, worsening an already fragile health system. A recent report from the World Health Organization [1] indicates that around 11 million people are in urgent need of healthcare services due to the ongoing conflict. The frequent attacks on health facilities and workers have become a barrier to accessing health services, especially for vulnerable groups such as pregnant women, children, and older people.

The International Committee of the Red Cross [2] reports that such attacks constitute a violation of international humanitarian law, which demands that medical staff and facilities be protected in case of armed conflicts. The violence resulted in the deaths and injuries of some of the health workers and disrupted emergency medical care. The Federal Ministry of Health in Sudan reported that multiple attacks have taken place against its workers, confirmed by the WHO to be a minimum of 46 incidents. The RSF has taken control of many hospitals, using them as military bases, disrupting essential services such as immunization, nutrition, deliveries, surgeries, and dialysis.

This means the patients have been transferred to other states; however, not all have managed to expand services for the transferred population, and the load on health facilities around the areas of conflict is likely to continue if the situation does not subside. Khogali and Homeida 2023 In Sudan, the outbreaks were getting worse and worse due to the war effects that had occurred in the country, with already high communicable disease rates. Diseases such as dengue fever and measles have spread quickly throughout six and four states, respectively, as the conflict disrupts surveillance, detection, and response efforts.

The ongoing war is worsening this situation by hindering the treatment of such diseases as malaria and cholera, which blossom in these overcrowded and unsanitary conditions. It is also worsening malnutrition, especially among children, due to disrupted food supply chains and destroyed facilities producing nutritional treatment products. The war also makes it hard for patients with noncommunicable diseases, such as diabetes and hypertension, to access medications; this implies the absence of treatment for chronic conditions. It is expected that, over the coming months, there will be an increased overall burden of disease and malnutrition due to the decline in the availability of medical supplies, limited access to healthcare facilities, and generally deteriorating social conditions. [3] Furthermore, the current mental health crisis worsens, especially among children. According to a report by World Vision dated 2024, it is estimated that the number of those who have been exposed to the acute mental health effects of the conflict will continue to grow dramatically as the cycles of hunger, trauma, and displacement compound.

Children are highly vulnerable to serious traumatization by the witnessed violence and unstable situation; this can lead to long-term effects on their psycho-physical maturation, cognitive development, social behavior, and emotional development. Since the conflict is continuous, the mental health needs of the population will continue to rise, further adding pressure on what is already a fragile healthcare system.

2.2. Socio-economic and environmental factors affecting healthcare delivery.

A number of socio-economic factors have a great bearing on healthcare delivery in Sudan. The main barriers are poverty and geographical challenges, especially in rural areas where healthcare is inaccessible. In these communities, there is a higher burden of disease due to poverty, political conflicts, and mismanagement of the available resources. Studies have shown that the low socio-economic strata are less likely to utilize formal healthcare services; those from poorer backgrounds are likely to experience problems of distance to healthcare facilities and

unaffordability. Besides, education levels are a critical determinant; individuals with primary education or less are less likely to use formal healthcare compared to those with higher education levels. Gender inequality is another factor that influences health care utilization, with males almost twice as likely to receive formal health care compared to females. Low levels of income, education, and income equality negatively impact the healthcare outcomes, such as maternal care, where rich and educated women are in a better position to seek healthcare services.
At the national level, the generally low financial endowments and small health budgets inhibit the effective implementation of health programs, especially those addressing NCDs.
Brain drain has been particularly problematic in rural areas, adding to the shortage of health professionals. This unequal access to health care across regions is even further perpetuated by unequal government spending on health, with Northern Sudan and Khartoum receiving far more health resources than Western regions [5; 6; 8; 12].

Environmental Factors Influencing Healthcare Outcomes in Sudan

Poor health conditions are linked to the environmental aspect of health care in Sudan, particularly pertaining to water and sanitation. In this respect, poor infrastructure, as well as limited access to clean water and improved sanitation, contribute directly to communicable diseases in the country, particularly those involving waterborne diseases such as diarrheal diseases. In 2017, only 37% of the population had basic sanitation, while 24% were still practicing open defecation. This implies that sanitation coverage in regions like Darfur, Kassala, and El Gadaref is particularly low, hence increasing disease transmission and promoting conditions such as schistosomiasis and soil-transmitted helminthiasis. Poor sanitation with limited access to sources of clean water increases the spread of diseases. This may be most commonly seen within farming communities, whose children are also at an advantage in diseases such as schistosomiasis because of the higher rates of exposure they have to infectious water sources. [9; 10; 13]
Climate also determines health status. Droughts, floods, and reduced rainfall amount to low crop yields and lead to food insecurity, hence worsening health conditions. In the rainy season, flooding results in diseases due to flooded waters, hence poor health status. [10; 11]
Conflicts in Sudan have also physically destroyed healthcare infrastructure, adding to inability to access health services. Such challenges are greatly felt in areas affected by the conflict, where even hospitals have been brought down, health workers displaced, and limited medication hence poor consistent care for the population served by such hospitals [8; 13]
The conflict has disrupted vital medical supply chains, halted disease surveillance programs, and suspended mental healthcare services. While critical infrastructure for water and sanitation has been compromised, the situation is further exacerbated by the suspension of international aid programs, including the UN World Food Programme. [14]

3. Disease Epidemiology in Sudan:

3.1 Common diseases and regional distributions

Sudan, having a tropical climate and going through a prolonged period of conflict and humanitarian crisis, has shown an immense burden both of infectious and chronic diseases. Such displacement of people into refugee camps and isolation has led to increased malaria, cholera, kala-azar, TB, and dengue fever. Chronic diseases have also increasingly affected these vulnerable populations [15]. This review updates the overview of the epidemiology, regional distribution, and outbreak dynamics of these diseases in view of the current war conditions in Sudan up to 2024 [16].

Malaria

1. Epidemiology and Regional Distribution

Malaria is one of the leading causes of morbidity and mortality in Sudan, with Plasmodium falciparum being the predominant species [15]. The climate is more favorable for mosquito breeding, with the highest transmission rates obtained in tropical and subtropical regions like Blue Nile, South Kordofan, and Darfur [16] . According to the Sudan Ministry of Health, 2024, conflict displacements lead to camp overcrowding and a lack of proper sanitation, which further fosters malaria transmission. In addition, seasonal rains and flooding favor ideal breeding of Anopheles mosquitoes. The seasonal rain and flooding enable breeding of Anopheles mosquitoes [17].

2. Outbreaks

The conflict has disrupted the programs on malaria control, hence increased incidence rates. In 2024, the host communities and refugees in Blue Nile and Darfur faced upsurge cases of malaria, with over 3,456 confirmed cases reported in Kurmuk by July this year [16]. Most of the patients did not have timely access to ACTs, hence higher mortality rates among the patients [17]. This is made worse by the rainy season, which expands breeding sites. Large-scale displacement due to the conflict has resulted in increased malaria transmission in very congested camps that lack ITNs. 3. Challenges and Control Efforts

Conflict disrupts malaria prevention programs and healthcare delivery. Limited access to ITNs and vector control measures, compounded by the destruction of health facilities, undermines malaria management efforts [17]. Efforts to control malaria are further hampered by the displacement of healthcare workers and logistical challenges in delivering essential supplies [19].

Cholera

1. Epidemiology and Regional Distribution

Cholera outbreaks are becoming increasingly common in flood-prone areas of Kassala and Al-Qadarif, as well as refugee camps in Darfur. In these locations, overcrowding, lack of access to clean water, and poor sanitation have created conditions that support the spread of Vibrio [20]

2. Outbreaks

A large-scale cholera outbreak started in mid-2024 and left at least 388 dead and around 13,000 infected after two months [21]. Refugee camps have also demonstrated a high infection rate because of the poor condition of their water sources and improper sanitation facilities [22].

3. Challenges and Control Efforts

The war has considerably affected the infrastructures of WASH-an important component for cholera control [20]. Emergency vaccination campaigns have been deployed, but logistical bottlenecks along with insecurity remain a limiting factor to their penetration. The wide destruction of infrastructures and health facilities has further complicated these response efforts.[22]

Kala-Azar (Visceral Leishmaniasis)

1 Epidemiology and Regional Distribution

Kala-azar is also endemic in areas such as Gedaref and Blue Nile. It is transmitted by sandflies and caused by Leishmania donovani.[20]

Malnutrition and the weakening of immune systems among the displaced population increase susceptibility. [23]. With the displacement of the population into these areas, exposure to sandfly vectors has increased, causing a surge in cases.

2. Outbreaks

In 2023–2024, there were over 2,000 cases in Gedaref, and the majority were refugees and IDPs [21]. Overcrowding and late treatment have resulted in high case fatalities [20]. The high case fatality rates can be attributed to late diagnosis and poor accessibility to antileishmanial drugs. Displacement and conflict have resulted in disturbed control programs and an increase in the incidence of kalaazar.

3. Challenges and Control Efforts

War conditions disrupt vector control programs and limit access to diagnostic and treatment resources. Co-infections with HIV further complicate kala-azar management [22]. Diagnostic and treatment resources are scarce, and co-infections with HIV further complicate management of health conditions [24].

Tuberculosis (TB)

1. Epidemiology and Regional Distribution

TB remains a significant public health issue, particularly in urban centers and conflict-affected regions. Malnutrition and overcrowding in camps exacerbate TB spread [23]. The displacement of populations into overcrowded camps has facilitated TB transmission

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2. Outbreaks

On the contrary, increasing burden of MDR-TB incidence is linked with disrupted health service and poor adherence to treatment within the displaced population. [20] Overcrowding along with displacement under unsanitary conditions in the refugee camps has favorably allowed TB to spread, acting as transmission reservoirs [21].

3. Challenges and Control Efforts

The war has disrupted TB control programs, including diagnostics and treatments. The stigma among refugees and internally displaced persons and irregular accessibility to medication adds to the poor health infrastructure that leads to resistance to treatment [24]. Destruction of healthcare infrastructures and displacement of healthcare professionals further complicate the control of TB.

Dengue Fever

1. Epidemiology and Regional Distribution

Dengue fever, transmitted by Aedes aegypti mosquitoes, is on the rise in both Kassala and the Red Sea due to poor waste management and urbanization. This, according to the Sudan Ministry of Health, has increased the population's exposure to Aedes aegypti mosquitoes, which are considered the major vectors of the dengue virus [19].

2. Outbreaks

Recent outbreaks reported more than 1,500 cases in Kassala in 2024 were largely in the peri-urban and refugee camp areas [18]. These are due to increased dengue transmission because of seasonal rain and lack of vector control.

3. Challenges and Control Efforts

The conflict has disrupted vector control and disease surveillance systems, undermining effective management efforts. Limited diagnostic capabilities and weak disease surveillance systems further impede response efforts and hinder effective dengue management. War conditions disrupt vector programs and public health awareness campaigns [22].

Chronic Diseases in Refugee Camps and Isolated Areas

1. Epidemiology and Challenges

Chronic diseases, including hypertension, diabetes, and cardiovascular conditions, are rising in refugee camps and isolated areas. Displaced populations face limited access to essential medications and regular care [21]. The ongoing conflict has disrupted healthcare services, limiting access to essential medications and routine care. Psychological stress, poor nutrition, and unhealthy living conditions worsen these conditions.

2. Impact of War

The destruction of health facilities and the forced migration of health professionals and workers have destroyed the care available for chronic disease management. "Psychological stress and suboptimal nutrition further exacerbates these conditions" [23]. The war had caused the displacement of millions; over 600,000 forced their way into countries bordering Ukraine. The resulting humanitarian crisis has swamped the healthcare systems to impede proper chronic disease management effectively.

3. Recommendations

WHO also adds that it is critical to strengthen health care systems through mobile clinics and telemedicine, integrating the care for chronic diseases into emergency response. Other key interventions should include mental health support and nutrition security interventions.

Conclusion

The epidemiology of diseases in Sudan thus reflects the devastating impact caused by conflict and displacement. The approach to these challenges must be improvement in coordination among humanitarian organizations, disease surveillance, and healthcare system strengthening [24].

3.2 Mental Health Problems.

The mental health among the displaced populations is a critical, yet very often overlooked, public health issue, especially in Sudan, where political instability and economic hardship and conflict have deeply affected vulnerable groups. Decades of civil unrest in Sudan has displaced millions, including school-aged children. This displacement disrupts access to education, healthcare, and social support; it exposes children to psychological trauma, separation from the family, and instability that can severely disturb mental health [26].

The mental health infrastructure in Sudan thus faces huge challenges as a reflection of decades of systemic underdevelopment and restriction of access to care. The Mental Health Act, which was drafted in 1998, was just approved in 2018; however, it still faces challenges for its implementation because of a lack of trained professionals and inequity in resource distribution [28]. Most psychiatric services are located within cities such as Khartoum and barely reach rural or conflict areas. From the 18 federal states of Sudan, only 12 have psychiatric hospitals with full equipment and consultant psychiatrists. This points out the critical gaps in access to mental health care. It underscores an urgent need for targeted interventions and particularly calls on the protection and care of children and adolescents affected by conflict.

Indeed, in the cross-sectional study of 963 Sudanese children and adolescents aged 11-17 years during the Sudan army conflict, Awad et al. [27] demonstrated that the prevalence of major depressive disorder was as high as 67.7%, and the majority of participants fell into the category of moderate to severe symptoms. The risk factors identified included age, sex, residency status, and trauma exposure. Females and older adolescents (17–18 years) were at higher risk of MDD, while internally displaced or living in conflict zones significantly increased the vulnerability. Personal experiences of traumatic events, such as serious injury, death, or loss of a close family member, were strongly associated with higher MDD scores, showing the deep mental health impact of conflict on this population.

The study also found a severe crisis in mental health, as 28.7% of respondents reported having thoughts of suicide almost every day [27]. This shocking fact underlines the urgent need to take immediate action toward meeting the mental health needs of conflict-affected children and adolescents. The researchers recommend implementing comprehensive mental health programs, including routine screenings, counseling, and access to psychiatric care, alongside training local health workers to provide culturally relevant support [27]. Such interventions are vital to mitigate the severe psychological toll of conflict and foster resilience and recovery among Sudanese youth.

In this vein, [25] also shared the findings of a survey conducted among 246 internally displaced school-age children in Ad-Damar to identify their main problems and required support systems for improving mental health and quality of life. The study showed a high prevalence of mental health issues among the children, with 68% frequently feeling sad, 73% feeling anxious, and 29% having been diagnosed with a condition like PTSD or depression [25]

It is important that infrastructure is strengthened and access to health is expanded in Sudan, with a view to leveraging innovative technologies for the identification, monitoring, and support of populations at risk. Machine learning solutions can enhance early detection, optimize resource allocation, and provide scalable digital interventions, especially in resource-constrained settings. Such technologies will be fully integrated into the mental health strategies of Sudan as part of mitigating the crisis and building a more resilient health care system in Sudan.

4. Machine Learning Applications:.

4.1. Traditional vs. ML-based disease surveillance

Disease surveillance enables immediate identification and, subsequently, rapid tracing of a disease within a region to avoid causing an outbreak through fast data collection and communication. Most of the traditional methods, until ages, have been associated with the physical collection, analysis, and reporting of information in manual forms. Their advantages are almost entirely overcome by shortcomings like high labor resource demand, low scalability, and possible latencies in reaching the recipients.

Machine learning-based systems have revolutionized outbreak detection and management by creating new avenues for real-time data processing and advanced analytical capabilities. This review discusses the development, comparative performance, and integration of traditional and machine learning-based disease surveillance systems, with a particular focus on the advantages, limitations, and potential to improve the responses of each system in the realm of public health.

Traditional Disease Surveillance

Traditional disease surveillance systems are those that rely on manual data collection, case reporting by clinicians, laboratory confirmation, and official reporting channels. These methods have been well entrenched and usually provide very accurate, validated data. However, they also have a number of considerable limitations, such as delays in aggregation, resource-intensive workflows, and limited scalability for high volumes of data [29].

Strengths:

- Very accurate and reliable because data is validated.
- Workflows are structured to monitor diseases within set protocols.

Weaknesses:

- Time-consuming and labor-intensive processes.
- Smaller capacity for real-time analysis of trends.
- Inefficiency in handling large datasets and the timely detection of anomalies.

Machine Learning-Based Disease Surveillance

Machine learning disease surveillance relies on automatic approaches to analyze a large volume of data from sources like social media, electronic health records, and web reports. Advanced algorithms such as Support Vector Machines, Deep Neural Networks, and Natural Language Processing are applied in these systems to detect anomalies in data and forecast outbreaks of diseases. [30]

Benefits:

- Real-time processing and scalability of data.
- Early detection of outbreaks with reduced delay.
- Ability to integrate diverse data streams for comprehensive analysis.

Limitations:

- Data quality dependency, requiring well-curated datasets.
- Ethical concerns regarding privacy and potential demographic bias.
- Continuous need for model recalibration as disease trends evolve.

Comparison and Insights

Traditional disease surveillance systems provide validated, structured data and are important in confirming disease outbreaks. However, they are mostly slow in processing and incapable of handling large volumes of data in real time. On the other hand, ML-based systems perform well in terms of the speed of anomaly detection and offer scalability by integrating diverse data sources. However, demographic bias and data privacy ethics are still an issue [31; 30].

Case Studies:

Twitter-based surveillance has also been successfully performed for diseases like influenza and dengue. [31].

HealthMap demonstrated significant effectiveness with the use of NLP in finding outbreaks of COVID-19 way before traditional systems.[29]

Conclusion

A well-thought-out integration of traditional methods with machine learning-based surveillance systems might be a highly promising approach for the enhancement of disease monitoring and outbreak detection. Using real-time data analysis and the power of sophisticated algorithms, ML-based systems overcome many of the shortcomings found in traditional approaches. Nevertheless, ongoing model refinement, assurance of data quality, and navigating ethical considerations all call for further research. It is only by adopting this hybrid approach, fusing traditional workflows with ML capability, that there can be a strong and responsive system of disease surveillance.

4.2. Benefits and limitations of ML in resource-constrained settings.(Alexa Bowman)

When implementing machine learning models, it is fundamental to consider any resource constraints. The success of the model and its implementation depends on the infrastructure & tools available. However, limitations can arise when the implementation exceeds available resources.

Tiny-ML-based systems have changed the accessibility of machine learning in resource-constrained environments because they allow machine learning models on devices with limited processing power to work with minimal energy consumption. [32]

Benefits

Machine learning technologies like Tiny ML offer benefits. Some benefits include:

- Latency: The data on Tiny ML devices does not need to be transferred between servers because they operate on edge devices. Data transfers generally take time, which causes a slight delay.
- Energy Savings: Tiny ML devices require very little power. This enables these devices to operate for long periods without recharging.
- Bandwidth Reduction: Little internet connection is needed for the interface/functionality. The devices contain "on-device" sensors that capture and process data on the device. No data needs to be delivered to an additional server.
- Data Privacy: Any data collected on a Tiny ML device stays on that device. There is no transfer of any data between devices, ensuring data privacy. [33]

Limitations

However, despite the benefits, there are some limitations to Tiny ML devices. Limitations Include:

- Resource Constraints: Tiny ML devices can last long without recharging. They have issues with maintaining algorithm consistency. This is because the maintenance of algorithms requires a lot of power.

- Hardware constraints: Deployment of Tiny ML devices on a wide scale is tedious and has many challenges. This is because every device has requirements, specifications, and algorithmic issues.
- Data Constraints: Traditionally, machine learning models can use datasets to train themselves. However, Tiny ML devices cannot train themselves this way because they collect data from external sensors. [34]

In conclusion When implementing machine learning models, it is essential to consider the technologies available, as the success of these models often depends on infrastructure. However, limitations can arise when computational power, storage, or energy are insufficient to meet the model's demands. TinyML has revolutionized machine learning in resource-constrained environments by enabling the deployment of models on devices with limited processing capabilities and minimal energy consumption.

4.3 Predicting outbreak epidemic disease with ML.

Machine learning reviews

Review for malaria

The need for an efficient healthcare system in Sudan is crucial to providing a quality medical service for people and controlling the outbreak of diseases. Healthcare researchers have been working hard to find solutions to similar health challenges around the world, especially in countries with high risks of vulnerability. Artificial intelligence and Machine Learning technology have been used to build models to predict future outbreaks of diseases such as cholera and malaria. In this paper two models were summarized, one model predicted malaria, and the other model predicted cholera. Both studies take place in Africa, in countries that are or have similarities with Sudan in geographic, environmental, and social problems.

The article "Prediction of Malaria Incidence Using Climate Variability and Machine Learning" analyzed and studied the malaria epidemic in six African countries in Sub-Saharan Africa. The countries are Burkin Faso, Cameroon, DRC, Mali, Niger, and Nigeria. The study of the research includes the feature engineering process to test the statistical significance of climate variability in malaria incidence and selects only relevant data, K-means clustering for outlier detection, and Extreme Gradient Boosting (XGBoost) algorithm for classification [34]. The study analyzes several climate factors, the number of malaria incidents, and the potential relation of those factors with the breakout of malaria. The features are precipitation, humidity, air temperature, sun radiation, pressure, and the number of malaria cases.

In general, the study finds a positive linear relationship between air temperature, precipitation, and the number of malaria incidents. In contrast, pressure has a negative linear relationship with malarian incidents. It is not a secret that mosquito habits depend on the environment, such as temperature and water. It is clear from these studies that differences in geographical locations and meteorological variables may affect malaria incidence in diverse areas and in various ways. Ultimately, understanding the degree of impact of climate variability on malaria incidence is of paramount importance [34].

In conclusion, this research can be approached to enhance decision-making to prevent future malaria outbreaks in advance. One limitation of this study is that the study only uses annual data but not real-time data. Another limitation is that the data used in the study is considered small. The researchers suggest that future research on this topic should include real-time data and the largest dataset to improve the predictive capability of the model [35].

Review for cholera

The article “How can Machine Learning Predict Cholera: insights from Experiments and Design Science for Action Research” conducted a study of several conditions that increase the risk of the outbreak of cholera epidemic. The researchers stated that the two most significant predictors of cholera are a lack of access to clean water and poor sanitary conditions. Other factors such as natural disasters, illiteracy, and internal conflicts that drive people to seek sanctuary in refugee camps may contribute to the spread of cholera [36]. The study analyzes how these factors correlate with the risk of an outbreak of cholera in Nigeria. A machine learning extreme-gradient boost algorithm is used to build a model to predict the risk of an outbreak of a cholera epidemic.

The data used in the research consists of three datasets, which include Yobe cholera data, socioeconomic data, and meteorological data. The features used in the cholera dataset are ID_Number, LGA, ward, settlement, name of patient, age (years), sex (M/F), date of onset, date seen at HF, date lab specimen taken, date sample sent to lab, results for RDT, and outcomes of alive, died, unknown, inpatient, outpatient. The meteorological datasets used consist of historical data, projected data, and general climate variability that include the monthly minimum, maximum, and mean temperatures, and precipitation. The Socioeconomic data UNICEF Data Warehouse was used to obtain annual state-level socioeconomic statistics from 2018 to 2021 including the percentage of people who have access to safe drinking water, the number of improved sanitation facilities available, and the number of basic hygiene facilities available. [36]

The methodology that researchers used in the model consisted of several steps. First, dimensionality reduction was applied to select only the most relevant features. Secondly, oversampling was used to address unbalanced data. Third, to check for outliers, since the outliers can affect the accuracy of the model. Finally, machine learning classifiers RF, NB, and XGBoost and 10-fold cross-validation were implemented.

The findings in the research concluded that the XGBoost algorithm performed well with an accuracy of 99.62%. The result signifies the model's proficiency in correctly classifying instances. The specificity and sensitivity scores indicate that 93% of the outbreak was correctly identified [36]. In addition, the researchers suggest the addition of big data and cloud computing practices that improve data capturing, storing, analyzing, and managing patient data should be included in future work (Ahmad Amshi et al., 2024). This can potentially improve the efficiency of the model for predicting the risk of future cholera outbreaks.

Review for Dengue fever

It is well known that dengue is one of the most common mosquito-borne diseases worldwide. According to Current Disses Control (CDC), this disease is caused by four distinct but closely related dengue viruses (dengue-1, -2, -3, and -4. In this review, the "Predicting dengue transmission rates by comparing different machine learning models with vector indices and meteorological data" is analyzed. This research examines the vector indices and meteorological data as predictors to develop the ML models [37]. The study uses seven machine learning algorithms: XG Boost, AdaBoost, Random Forest, logistics regression, Naïve Bayens, decision tree, and support vector machine.

This study used data from the Entomology and Pest Unit, Health Department of Federal Territory of Kuala Lumpur & Putrajaya, Malaysia. which include house index (HI), Breneu index (BI), container index (CI) and premise index (PI) from January 2018 to December 2020 in five districts, namely Titiwangsa, Kepong, Cheras, Lembah Pantai and Putrajaya [37]. The other parameters used came from the Malaysia Meteorological Department, which includes rainfall, humidity, barometric pressure, and maximum temperature. The target used is the dengue transmission rate.

The methodology used to start with selecting the most important variables. The Boruta algorithm was implemented to select all the most relevant variables. The seven machine learning classifiers were implemented and evaluated. The under curve-AUC was used to evaluate the performance of the classifiers and F1-score.

In conclusion, the study results indicated that the meteorological data were more important than vector indices, HI being the most important vector indicator and CI the less important variable. Based on the results of the matrices, XGBoost is the ML algorithm that has the greatest performance among the algorithms in this study with a roughly .82 under curve-AUC and .78 F1-score precision. The article points out that this study has limitations that need to be addressed for future studies. For example, the vector indexes of pupal index and the adult index might be a better indicator as it is closely linked to the adult population [37]. Also, the dataset was relatively small.

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