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Revolutionizing Healthcare: The Role of AI-Based Medical Expert Systems in Building a Better Future

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Abstract— Modern society has an increasing need for better architecture and medical care. However, this difficulty is not sufficiently addressed by present medical architecture. The Medicinal Expert technique can be used to help persons in need in order to address this issue. A tremendous amount of medical data, including patient medical histories, records, and new medications, can be managed and maintained using this technology. It can help with decision-making and fill in for specialists when they are not present. The Medicinal Expert approach is a complex computer software system that generates forecasts using empirical data and expert knowledge. Based on the available training data and knowledge base, these systems function intelligently. Additionally, there are numerous Medical Expert System tools that support clinicians, help with diagnosis, and are crucial for instructing medical students. In this study, we introduce an AI-based Medical Expert System, its features, and its potential to help patients and medical students. We also go through some key findings from recent and prior research on expert systems, as well as how these systems can make the world a better place.

Keywords- Disease diagnosis, Medical Expert System, Machine Learning, Disease Prediction, Knowledge Base, Artificial intelligence, etc.

I. INTRODUCTION

Machine learning is a prominent subfield of artificial intelligence (AI), which is an essential element of the healthcare sector. Numerous links and correlations between disease, health, and patient data can be made by machine learning algorithms. Recent developments in the field of machine learning have made it possible to generate new diagnosis and treatments while also facilitating simpler access to healthcare in underdeveloped nations.

Expert systems are one of the notable applications of AI in healthcare. These are computer programmes created to mimic the capability of a human expert with knowledge in a certain topic to make decisions. In order to assist users in resolving certain issues within a given field of study, expert systems were developed. They ought to include explanations, a user interface for interacting with users, and data visualisation. One system that includes all these needs is the medical expert system.

A collection of software applications referred to as medical expert systems function in conjunction with a medical knowledge base. Any medical expert system's main objective is to identify a patient's ailment, support their recovery, or advance their overall health and wellness. The system is intended to help healthcare professionals' decision-making by utilising its knowledge and analytical capabilities, thereby improving patient outcomes.

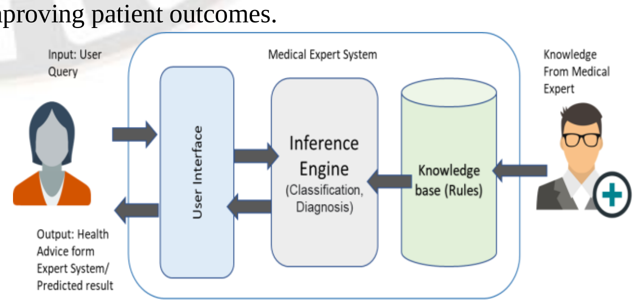

Fig. 1: Schematic of a Medical Expert System Architecture

A user interface, an inference engine, and a knowledge base are the three essential parts of a medical expert system. The knowledge base acts as a clearinghouse for all the important data and expertise needed for decision-making. It contains data from many different sources, including as clinical guidelines, academic research, and expert opinions. It may also include a patient database to hold patient-specific information. Applying reasoning and decision-making rules to the data kept in the knowledge base is the responsibility of the inference engine. It uses a variety of algorithms and methods to process input data, producing output. The user interface, which allows users to interact with the system, can be customised to meet the demands of various user types, including patients, doctors, and nurses. Features like data entry, data visualisation, and decision support could be present. Overall, a medical expert systems architecture strives to help healthcare professionals and patients' ability to make correct and trustworthy decisions by facilitating disease diagnosis, treatment recommendation, and personalised care based on patient data and medical expertise.

II. LITERATURE REVIEW

In terms of error metrics, Sharma's heterogeneous ensemble forecasting model proposed in 2021 outperformed state-of-the-art ensemble models [1]. Integrating divergent projections and merging information from various sources will become increasingly necessary as more outbreak data is connected to public health data repositories to obtain the most accurate prognosis of an unfolding disease epidemic.

Singh's Effective Heart Disease Prediction System (EHDPS) presented in 2014 utilized the Multilayer Perceptron Neural Network (MLPNN) and the Backpropagation (BP) algorithm based on Artificial Neural Network (ANN), with the MLPNN model offering superior results and assisting domain experts and medical professionals in planning for better and earlier patient diagnosis [2]. Elngar proposed an intelligent system for skin disease prediction using machine learning in 2021 to provide fast and low-cost medical treatment, reducing the problem of skin disease spread and offering better techniques to detect skin problems [3].

Subaeki built an application for vertigo disease diagnosis in 2017 to make it easy for people to obtain and convey information anytime and anywhere economically, providing diagnostic facilities for users to diagnose the possibilities of users having vertigo and offering additional information apart from doctors about vertigo [4]. Chebanenko applied the cluster analysis to process data on patients for therapy in 2020 [5].

Muslim described the E-Expert application in 2018, which compares the patient's determined information with the decision table for an expert mapping development system with disease searching symptoms based on ICD 10 [6]. According to Goita in 2021, knowledge of pathogen agents, their modes of transmission, their evolution, and the effects they cause, as well as the actions to be taken in terms of research on health issues, vaccination, and medicinal parameters, is the most effective weapon against any pandemic [7]. Ahmad adopted the Average Drop Gini in 2017 to determine the relevance of each attribute in the diagnostic decision support system of chronic kidney disease using a support vector machine [8].

Ananthi examined the performance of categorized groups in predicting cardiac and renal effects of diabetes clinical data using the recommended fuzzy classification system consisting of three phases in 2017 [9].

Although estimating the glomerular filtration rate based on cystatin C and blood creatinine concentrations represents a substantial advancement in the diagnosis and monitoring of chronic kidney disease (CKD), it has significant limitations, including poor performance in forecasting the course of CKD and limited discriminatory power in determining whether individuals have early CKD. Research in this area is focused on finding novel biomarkers that serve as superior GFR indicators or signal early renal tissue damage to enable more accurate early detection of CKD [10].

III. OBSERVATION ON SURVEY

It has been found that disease prediction is attainable using several ML techniques and algorithms. The field of medicine and diagnosis are being affected by machine learning. The proposed expert system is able to suggest a problem-solving approach that is both simple and cost-effective. In this study, predictions are made using a variety of methodologies, but the accuracy of these performances is compared to find the optimum prediction system.

The development of an expert system places more emphasis on increasing accuracy and decreasing diagnosis time. These expert systems can detect the disease early and assist in its easy cure. Diseases of specific body components, such as the heart, liver, and kidney, are extremely threatening to human life and may result in death if discovered at an early stage. Additionally, some of these systems have extra elements that offer treatments or remedies in accordance with the stated diagnoses. To recommend the most efficient therapies, these features draw on the knowledge base of medical specialists and machine learning techniques.

There are systems that try to make it easier for patients to connect with doctors in addition to those that deal with diagnosis and treatment. The process of making appointments and obtaining medical care is streamlined by these systems' use of machine learning algorithms to connect patients with clinicians in accordance with their specific medical requirements and preferences.

Overall, these websites and mobile applications show how machine learning has the potential to enhance patient experience by more successfully bridging the gap between people and medical experts, as well as to increase the speed and accuracy of disease diagnosis and treatment.

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Table 1: Comprehensive Review of Literature on Medical Expert Systems

Year	Dataset Used	Methodology/Algorithms	Accuracy/Result	Future Scope
2021[1]	Monthly disease data	Preprocessed using log and Z-score	Ensemble Model reduced MAE by 3.07%, 11.58%, 27.18%, 13.46% for dengue, food poisoning, tuberculosis, and chickenpox respectively	Identification of specific diseases; potential for further disease identification
2018[2]	Heart Disease dataset	Multilayer perceptron neural network	Accurate prediction of heart disease risk	Applicability for medical students
2021[3]	Skin Disease Dataset	CNN-SVM-MAA system with CNN and SVM	Mobile app aiding in skin illness identification	Mobile application usage; extended use cases
2020[4]	Vertigo Disease Dataset	Backward Chaining and DFS	Software for diagnosing vertigo probability and providing additional information	Enhanced information dissemination about vertigo
2020[5]	Cardiovascular Disease dataset	Cluster Analysis	Statistical calculation of treatment effectiveness based on patient compliance	Treatment effectiveness analysis
2019[6]	Disease Dataset from Indonesia	Anamnesis and Matching technique	OpenEHR-based diagnosis system aiding users and doctors in disease diagnosis	Knowledge acquisition and consultation process facilitation
2021[7]	COVID-19 disease Dataset	Model-oriented, object-oriented, rules-based, case-based approaches	Detection of COVID-19 based on symptoms; inclusion of supplementary examination analysis	Enhanced system functions for more effective patient outcomes
2017[8]	Chronic Kidney Disease Dataset	Classification Modeling and SVM	Intelligent system for identifying patient conditions	Support for medical students in patient condition identification
2017[9]	Diabetes mellitus dataset	Fuzzy Classifiers	Prediction of kidney and heart problems due to diabetes mellitus	Early detection of diabetes-related complications
2017[10]	Chronic Kidney Disease dataset	Artificial Intelligence	Smart expert system for kidney disease diagnosis	Patient understanding of renal health status

IV. MACHINE LEARNING METHODOLOGIES FOR CLASSIFICATION

1. Support Vector Machine (SVM):

In several domains, including medicine, Support Vector Machine (SVM) is a well-liked supervised learning machine learning technique for classification and regression analysis [11]. In cancer diagnosis models, SVM has been used to scale each attribute to a range of [0, 1], then divide the pre-processed data into training and testing datasets [12].

Measures like specificity and sensitivity are frequently used to assess how well the SVM classifier performs in differentiating cancer patients from non-cancer controls [13].

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2. Decision Tree (DT):

A common machine learning method utilized in the creation of medical expert systems is the decision tree algorithm [14]. Based on input data, a tree-like model of decisions and potential outcomes is created.

Decision trees can be applied to a variety of activities in the medical field, including disease prognosis, treatment planning, and diagnostic [15]. The decision tree algorithm begins by choosing the dataset's most pertinent attribute to act as the tree's root node. The values of the chosen property are then used to divide the data into smaller groupings. Up until a leaf node, which symbolizes the ultimate choice or result, is reached, this procedure is repeated recursively for each subset.

For instance, the decision tree might include patient information such as symptoms, lab findings, and medical history in a diagnostic system for a certain disease. The algorithm would choose the most important characteristic, such the patient's age, then divide the population into two branches according to whether they fall above or below a predetermined age threshold. Up until a leaf node with a final diagnosis is reached, the algorithm would divide the data depending on additional pertinent qualities, such as the existence of particular symptoms [16].

3. Neural Networks:

Medical expert systems may analyze and forecast medical data using neural network designs. Different neural network architectures can be applied to a range of applications, including time series analysis, natural language processing, and picture classification.

The convolutional neural network (CNN) is one type of neural network design that can be applied in medical expert systems. For analyzing medical pictures like X-rays, CT scans, and MRIs, CNNs are very helpful. Convolutional filters are used to extract features from the image, and these characteristics are then used to classify the image into other categories. CNNs have been applied in a number of medical settings, including the detection of breast cancer in mammograms and the prognosis of Alzheimer's disease progression from brain MRI images [17].Another form of neural network design that can be applied in medical expert systems is recurrent neural networks (RNNs). Electrocardiograms (ECGs), electroencephalograms (EEGs), and patient vital signs are examples of time series data that RNNs are particularly good at analysing. Using the prior outputs as inputs for the subsequent input, RNNs process each input in the time series sequence. Numerous medical applications have made use of RNNs, including forecasting ICU patient outcomes and spotting epileptic convulsions in EEG data [18].

To perform tasks like forecasting illness risk and drug discovery, medical expert systems can also use other neural network architectures, such as feed forward neural networks and deep neural networks [19]. Overall, neural network architectures offer a formidable tool for deciphering and forecasting from medical data, and they have the potential to greatly increase the precision and effectiveness of medical diagnosis and therapy.

V. EXPERIMENTATION AND RESULT

A. Dataset Preparation:

We employed the dataset by KAUSHIK268 (2019) [20] titled "Disease Prediction Using Machine Learning." This dataset comprises 133 columns and 4920 instances. It encompasses a diverse range of health-related attributes, including age, gender, blood pressure, cholesterol levels, heart rate, and various other relevant metrics. Among the 133 columns, 132 pertain to symptoms experienced by patients, while the last column indicates the prognosis. The primary objective of this dataset is to leverage machine learning algorithms to forecast the presence or absence of a specific disease based on these feature attributes.

Features such as "vomiting," "fatigue," and "high fever" have exhibited the presence of outliers. The subsequent figure 2 illustrates the box plots depicting the distribution of these features and the identification of outlier data points within their respective distributions.

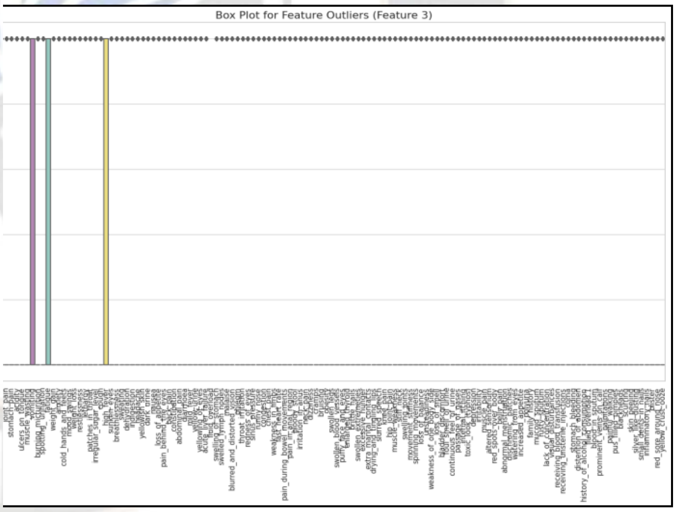

Fig 2: Box Plot for Other Feature Outliers

B. Model Evaluation:

Several predictive models were assessed using the designated dataset for medical disease prediction, including 'Logistic,' 'Decision Tree,' 'Random Tree,' 'SVM,' 'Naive Bayes,' and 'ANN.' The subsequent Figure 3 illustrates a comparison of the accuracy achieved by each of these models.

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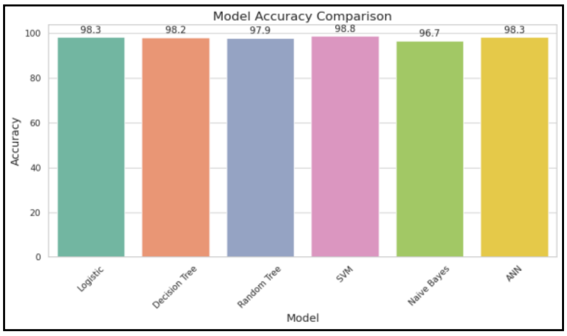

Fig 3: Box Plot for Other Feature Outliers

C. *Confusion Matrix*

In a binary classification problem, let TP, FP, TN, and FN represent the number of true positives, false positives, true negatives, and false negatives, respectively.

In medical contexts, the consequences of false positives and false negatives can be significant. The confusion matrix helps clinicians and researchers understand the potential impact of the model's predictions on patient care and make informed decisions about interventions, treatments, and further testing.

Then, we may determine the evaluation metrics listed below.

Accuracy = (TP+TN)/(TP+FP+TN+FN)

Precision = TP/ (TP + FP).

Recall (sensitivity) = TP/(TP + FN).

True negative rate (specificity) = TN / (TN + FP)

F1 score = 2 * (precision * recall) / (precision + recall)

We can evaluate the effectiveness of our model and identify areas for improvement using these assessment metrics and the entries of the confusion matrix. A high rate of false positives, for instance, would indicate that our model is extremely sensitive and has to be modified to lower false positive rates. Conversely, a high number of false negatives may suggest that our model is overly conservative and needs to be tuned to reduce false negatives.

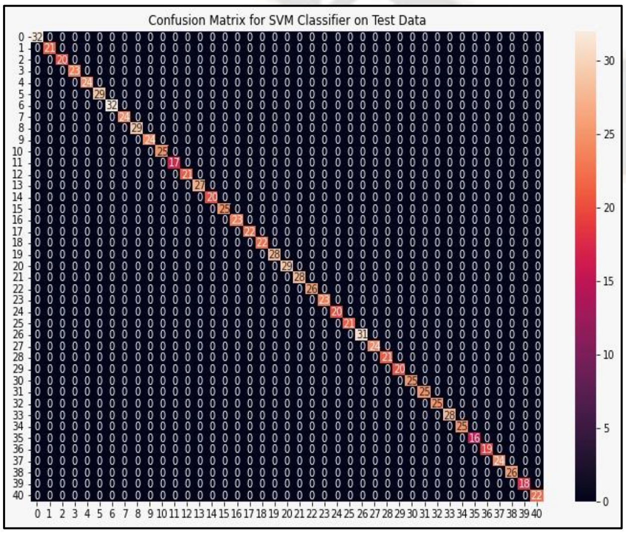

Fig. 4: Confusion Matrix of HealthMate for Disease prediction

VI. RESULTS AND OUTCOME

Upon successfully implementing the model, a total of 41 random samples were drawn from the testing dataset. In this process, the SVM classifier demonstrated a high accuracy rate of 98.8%. This accuracy was duly substantiated through the examination of a confusion matrix and a comprehensive classification report.

Figure 5 showcases the user interface of HealthMate, where users can input and communicate their symptoms. This application engages in a thorough analysis of the provided symptoms, subsequently predicting potential diseases and offering corresponding medical recommendations. Furthermore, the application takes into account historical health information, encompassing prior conditions such as hypertension, diabetes, and cardiac ailments. Medical records of patients are systematically managed, necessitating manual uploading of relevant files and reports by the user.

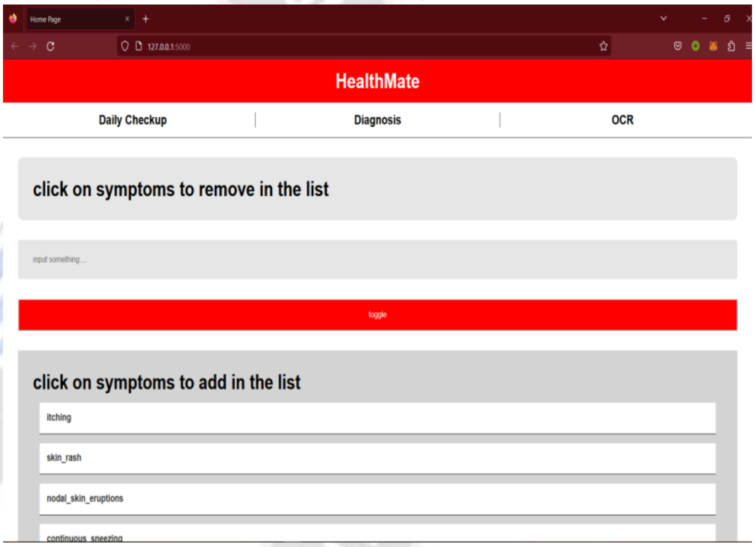

Figure 5: HealthMate Interface for Inputting Symptoms

Figure 5: Daily Check up Interface of HealthMate

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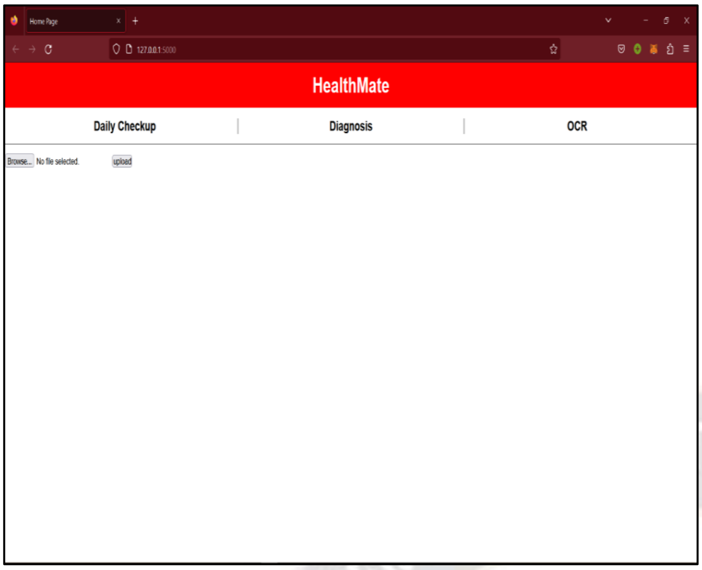

Figure 6: Interface for Report Evaluation through OCR

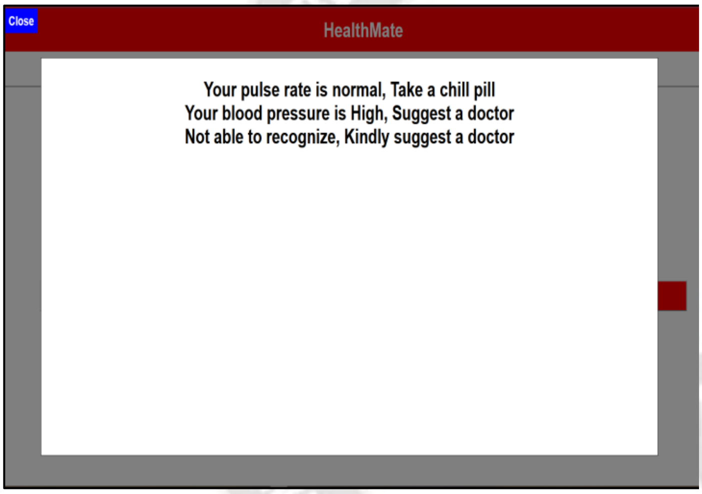

Figure 7: Diagnostic result generated by HealthMate (Ex. 1)

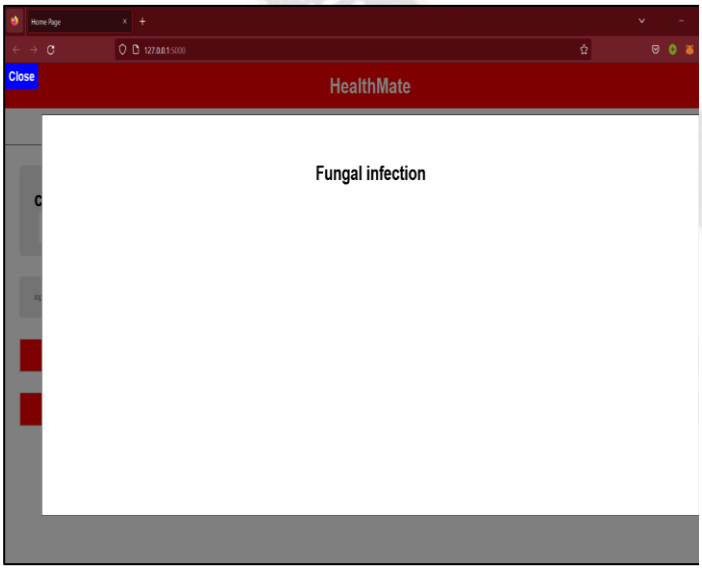

Figure 8: Diagnostic result generated by HealthMate (Ex. 2)

CHALLENGES

If/when any study or research is done in the domain of health diagnostics or healthcare it is very important to be precise with the outputs and avoid inappropriate results and also manage the health data securely and properly. During the survey, we identified a few challenges that generally need to be faced during any project or work in the healthcare domain. Managing health data with proper security and maintaining accuracy are two major challenges. Along with it, there might be various smaller problems to tackle also, but again solutions for such problems can be drawn specifically to the research or work. So it would not cause any problems. The project's requirements evolve from what they were at the start, but again solutions for such problems can be drawn specifically through research and teamwork.

V. CONCLUSION

This paper focuses on the contributions of expert systems in the healthcare domain, specifically in medication suggestions and disease treatment. The paper provides insights into the development of expert systems, including the knowledge base, database, and machine learning models. The importance of relevant and adequate data for the expert system is emphasized as it forms the basis of the system. The paper also discusses the necessary approaches required for building a model, such as machine learning algorithms like random forest, decision tree, neural network, and support vector machine, and analyses their advantages and disadvantages to select the most appropriate technique for optimal efficiency. The paper also highlights the challenges faced during the construction of these systems and investigates various databases and other related areas in the expert system domain. The system gives higher accuracy for prediction of disease using the SVM classifier by setting various hyperparameters of the model. The use of a patient's medical history also contributes in suggesting various precautionary measures.

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