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AI Powered Medical Diagnosis and Disease Support System

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Abstract - *Machine learning's use in healthcare has created new opportunities to support medical diagnosis. In this study, a system that uses user-provided symptoms to forecast diseases is presented. A dataset of symptoms and related disorders is used to train the model using supervised machine learning methods including Support Vector Machine (SVM), Random Forest, and Decision Tree. Users can enter symptoms and get immediate forecasts thanks to an intuitive interface created using Streamlit. By serving as an initial diagnostic tool, this system aims to raise users' awareness of possible health problems. Through the provision of an easy-to-use platform, the system illustrates how machine learning may be incorporated into healthcare processes to enhance health literacy and early diagnosis. Additionally, the modular architecture enables future improvements, enabling it to be tailored to new datasets and medical requirements.*

Key Words: **AI diagnostics, symptom checker, disease prediction, machine learning, healthcare technology, clinical decision support, medical AI, patient triage, Streamlit application, open-source healthcare**

1.INTRODUCTION

Medical diagnosis frequently calls for in-depth knowledge and meticulous analysis of clinical findings, patient history, and symptoms. However, machine learning has a chance to help with faster and more accurate disease diagnosis given the abundance of health data already available. The goal of this project is to create a system that predicts diseases based on user-input symptoms using machine learning techniques. The system serves as a first point of reference, directing consumers toward qualified medical assistance as necessary, rather than trying to replace doctors.

Three machine learning models—SVM, Random Forest, and Decision Tree—were put into practice and their accuracy and efficiency were evaluated. Users may easily interact with the models thanks to the solution's deployment via Streamlit. The strategy focuses on offering a diagnostic tool that is easy to use, scalable, and accessible.

1.1 Motivation

Due to uncertainty or delayed access to medical services, people frequently put off getting medical counsel. Many patients wait until symptoms develop, even though early disease discovery can significantly enhance treatment outcomes. The requirement for an approachable platform that can provide initial insights based on symptom analysis is what spurred this research.

Machine learning models are used to provide customers with quick, data-supported forecasts that encourage additional medical research. Additionally, offering a straightforward web approach lessens dependency on unreliable internet sources that could provide false information. The system encourages users to seek prompt professional medical care by providing a systematic and scientific approach to symptom analysis.

1.2 Objective

Create a system that uses machine learning to forecast illnesses based on their symptoms.

1.Train and assess several models, including SVM, Random Forest, and Decision Tree.

2.Use Streamlit to create a web interface that is both interactive and lightweight.

3.Give users prompt, trustworthy diagnostic recommendations.

4.Evaluate the performance of the models and choose the best one to implement.

5.Allow for quick model upgrades and ongoing improvement as new data becomes available.

6.The ultimate goal is to offer a preliminary diagnostic instrument that can help people comprehend potential health issues.

1.3 Scope

Using a preprocessed and structured dataset, this system is intended to make disease predictions based just on symptom input. It does not take the role of thorough clinical evaluation, even though it covers a wide spectrum of common disorders. Although the present version uses a static dataset, it may be extended in the future to include more diseases, symptoms, or individualized health information.

Support for many languages, integration with patient history for better predictions, and the release of mobile applications are examples of potential future enhancements. The system can adapt over time to handle more datasets and more diverse healthcare settings because to scalability and modularity.

2. UNDERSTANDING MEDICAL DIAGNOSIS

The process of identifying the illness or condition that best accounts for a person's symptoms and indicators is known as medical diagnosis. Traditionally, medical experts who rely on clinical knowledge and experience do this role. Nevertheless, machine learning algorithms can help with this process by examining big datasets to find trends and connections between illnesses and symptoms.

These AI-powered tools aid in cutting down on diagnostic time and mistakes, particularly in the early stages when symptoms may be hazy. It becomes feasible to automate preliminary evaluations and recommend likely ailments by utilizing algorithms trained on medical datasets. Therefore, in settings with limited healthcare resources, machine learning can be used as a supporting tool to improve the effectiveness and precision of clinical diagnosis.

2.1 Data Science in Healthcare

Advanced analysis of medical data has been made possible by data science, which has been essential in transforming healthcare. In this experiment, machine learning models were trained using a dataset that connected symptoms to illnesses. To prepare the dataset for precise model training, data preprocessing procedures such feature encoding, addressing missing values, and dividing the data into training and testing sets were crucial.

While SVM determines the best decision boundaries for classification, algorithms such as Random Forest and Decision Tree learn from patterns in the data. Metrics like accuracy, precision, and recall are used to evaluate models, guaranteeing that the predictions are accurate in a variety of situations. It is anticipated that the system's prediction powers will advance even more as it is continually enhanced with fresh data.

2.2 Data Visualization for Medical Diagnosis

A crucial component of making machine learning predictions understandable and approachable is visualization. For this research, visual representations including confusion matrices, feature significance plots, and model accuracy graphs were made using libraries like Matplotlib and Seaborn.

Developers can better evaluate model performance and pinpoint areas for development with the aid of these images. Users can gain confidence in the system's findings by understanding which symptoms were most important in a prediction thanks to clear displays. Transparency is further supported by clear graphical display of results, which facilitates understanding of the diagnostic procedure and results by both technical and non-technical users.

2.3 System Design and Methodology

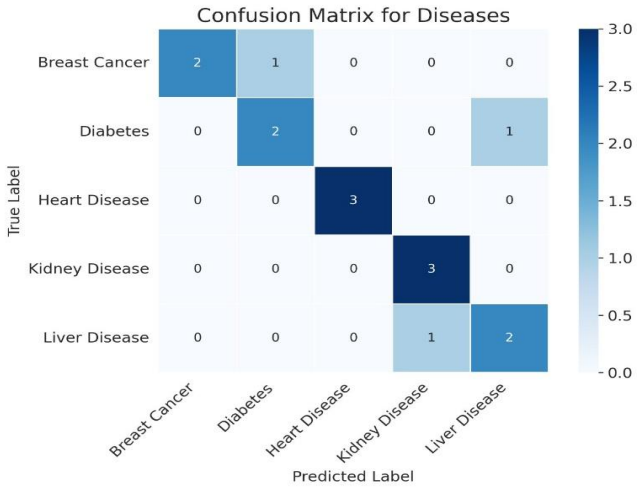


Figure 2.3.1: Confusion Matrix showing classification accuracy between predicted and actual disease classes.

A confusion matrix that assesses a disease prediction model's performance is shown in the image. It contrasts the model's predictions with actual diseases (true labels). Errors are displayed off the diagonal, and accurate predictions are displayed along it. For instance, twice breast cancer predictions were accurate, but once it was mistakenly identified as diabetes. With three accurate predictions apiece, heart disease and kidney disease both had flawless prediction rates. Two of the forecasts for liver illness were accurate, but one for renal disease was not. Higher prediction numbers are shown by darker blue hues. The density of forecasts can be seen with the aid of the side colour bar. This matrix aids in determining the model's advantages and disadvantages; it performs well for renal and heart disorders but highlights some confusion between other problems.

3. RELATED WORK

3.1 Literature Survey

Shinde et al. (2021) [1] created a deep learning model that prioritized explainability in addition to achieving high cancer diagnostic accuracy. Their program, which aims to detect tumors early, identified breast cancer with an astounding 89% accuracy rate. They underlined that interpretable and transparent AI systems can help physicians establish trust, which will improve the use of AI in actual healthcare settings.

The application of AI in critical care and emergency situations was thoroughly investigated by Montassier et al. (2021) [2]. According to their analysis, AI models have the potential to increase diagnostic precision and assist physicians in making quicker, potentially life-saving judgments. To guarantee that AI technologies function dependably in actual emergency situations, they additionally emphasized the necessity of additional clinical trials and improved data integration.

The use of machine learning models, such as decision trees and random forests, in medical emergencies was investigated by Hsia et al. in 2021[3]. According to their analysis, AI technologies can greatly speed up reaction times and increase the precision of critical condition diagnosis. They did stress, though, that in order to guarantee these systems' efficacy under strain, extensive real-world validation is required.

In their 2021 study, Zhang et al [4]. examined how AI may be used to identify COVID-19 through medical imaging such as CT scans and chest X-rays. They emphasized how AI models helped detect COVID-19 infections early during the pandemic by quickly increasing diagnostic accuracy. They cautioned about issues including small datasets and false positive risks, particularly in varied groups, despite the advancements.

Jiang et al. (2020) [5] examined the application of AI technologies to medical imaging tumor subregion analysis. They noted that AI can identify minute patterns that are frequently overlooked by human sight, increasing the precision of cancer diagnosis. While addressing difficulties such as the intricacy of medical data, the assessment also covered the integration of AI with conventional diagnostic tools to improve treatment planning.

A scoping assessment assessing the integration of AI into clinical workflows, particularly in medical imaging, was carried out by Shen et al. (2020) [6]. They discovered that deep learning models have a lot of promise for the diagnosis of neurological conditions and cancer. Nonetheless, the study emphasized that concerns like data privacy, transparency, and legal obstacles need to be resolved if AI is to be successful therapeutically.

Amisha et al. (2019) [7] emphasized the value of explainable AI (XAI) in medical imaging and how openness in AI models can increase patient and healthcare provider trust. Their survey categorized several XAI techniques and described how each improves deep learning systems' interpretability. The authors emphasized that comprehensive explanations are essential for AI to be generally accepted in clinical diagnosis, particularly for disorders like cancer and cardiovascular ailments.

Topol (2019) [8] investigated how healthcare might become a more individualized and effective system by integrating AI and human intelligence. He underlined the necessity of striking a balance in medicine between automation and human interaction. The influence of AI on patient outcomes, workflow, and diagnosis was discussed in the paper. Topol also talked about how integrating AI into healthcare practice requires ethical considerations and openness.

An extensive study of AI applications in breast cancer diagnosis and detection was carried out by Zhang et al. (2019) [9]. Their research looked at machine learning models that are used to analyze clinical records, biopsies, and mammograms. According to the study, AI lowers diagnostic errors and increases the accuracy of early-stage cancer detection. AI has a lot of promise to improve breast cancer screening and treatment choices, the scientists stressed.

De Fauw et al. (2018) [10] demonstrated DeepMind's AI system, which demonstrated accuracy on par with that of skilled physicians in identifying eye conditions including diabetic retinopathy. The AI, which was trained on hundreds of retinal scans, assisted in early illness detection and therapy. This study showed how AI has enormous potential to help specialized medical disciplines and reduce the effort for medical practitioners.

An AI system developed by Rajpurkar et al. (2018) [11] that can identify arrhythmias from ECG data with performance comparable to that of skilled cardiologists was shown. The program accurately identified several types of arrhythmias using a dataset of over 64,000 ECG recordings. Their research demonstrated how AI may greatly enhance cardiac care. Real-time ECG interpretation in clinical and telemedicine settings may be supported by this technology.

Ching et al. (2018) [12] examined the potential and difficulties of using deep learning in biology and healthcare. Imaging, genomics, and EHR-based applications were the main topics of their review. The authors emphasized the significance of clinical validation, transparent models, and strong datasets. They came to the conclusion that in order to fully utilize AI in medical research and diagnosis, interdisciplinary cooperation is essential.

Shen et al. (2017) [13] reviewed in depth the applications of deep learning, and CNNs in particular, in medical imaging to diagnosis conditions including diabetes and lung cancer. They emphasized the accomplishments to date while simultaneously drawing attention to present drawbacks, including a lack of data and difficulties with model generalization. To solve these problems and fully utilize AI's promise in clinical diagnostics, the authors urged more research.

A deep neural network was shown by Esteva et al. (2017) [14] to be able to classify skin cancer with an

accuracy level on par with board-certified dermatologists. Their AI model effectively differentiated between benign and malignant tumors after being trained on more than 129,000 clinical pictures. The study demonstrated AI's potential for remote diagnosis and treatment. This study demonstrated the potential of deep learning to aid in the early diagnosis of skin cancer, especially in environments with limited resources.

In their discussion of deep learning's application to diagnostic imaging, Lakhani and Sundaram (2017) [15] emphasized AI's capacity to identify cancer, fractures, and lung disorders. The importance of edge computing for data processing in clinical contexts was highlighted by the study. Their results demonstrated how AI may help radiologists and expedite image interpretation. They came to the conclusion that AI enhances medical imaging rather than replaces it.

4. PROPOSED MODEL

4.1 Workflow

A web interface is used to choose symptoms by the user at the start of the suggested system workflow. A trained machine learning model receives these symptoms after they have been transformed into binary values. The most likely diagnosis is returned by the backend after using this input to calculate probability for different conditions. Additionally, the system recommends lifestyle modifications and pertinent medical recommendations. Streamlit facilitates the HTTP queries that the interface uses to communicate with the backend.

Inference is handled by the ML model, and the outcome is shown instantly. Data about user interactions is recorded by a logging system for further analysis and retraining. The entire process, from symptom input to disease prediction and result feedback, is depicted in Figure 1 below.

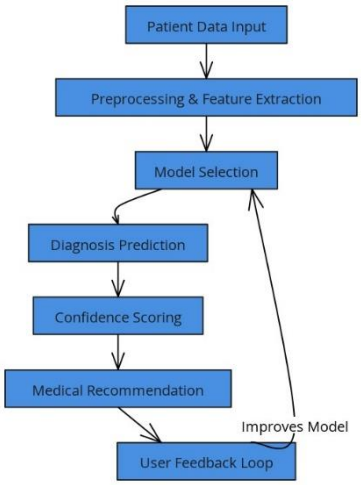


Figure 4.1.1: System Workflow Diagram

4.2 Techniques Used

The system combines a number of machine learning methods, such as SVM, Random Forest, and Decision Tree Classifier. Scikit-learn is used for training and assessment, while Python tools like Pandas and NumPy help with data management. Feature selection, handling null values, and binary symptom encoding are all examples of data preprocessing. Cross-validation and grid search are used for model tuning.

Evaluation charts are created using visualization frameworks like Matplotlib. Quick UI development and interactivity are made possible via the Streamlit framework. Because of its scalable design, the system can be expanded onto mobile platforms or integrated with cloud services.

4.3 Implementation Details

The project's frontend, which uses Streamlit, provides an easy-to-use interface for diagnosing and choosing symptoms. The Python-developed backend logic controls real-time prediction, model training, and dataset loading. Symptom-disease pairings are extracted from structured CSV data. Supervised learning with accuracy validation is used to train each machine learning model.

Joblib is used to save models, which are then loaded during runtime to guarantee quick execution. Session timeouts and form validation are examples of security features. Compatibility between platforms is guaranteed

4.3.1 Symptom Analyzer Module

Symptom Analyzer interface screenshot showing real-time prediction display and multi-select symptom input

Users can enter symptoms from a pre-made list using this module. After processing these inputs, the interface

transforms them into a format that the machine learning model can comprehend. The module uses prediction scores and symptom relevance to rank possible diseases. Additionally, it provides explainability by with a Docker-based containerization architecture, and automated testing is done with GitHub Actions. While Heroku or Streamlit Cloud can be used for production deployment, localhost deployment makes debugging simple. deployment, localhost deployment makes debugging simple. Highlighting the most important symptoms that contribute to the diagnosis.

Other features include a help area that explains medical words and symptom classification (e.g., respiratory, digestive). With this module, users can enter symptoms from a list that has already been created. After processing these inputs, the interface transforms them into a format that the machine learning model can comprehend. The module uses prediction scores and symptom relevance to rank possible diseases. Additionally, it provides explainability by highlighting the most important symptoms that contribute to the diagnosis. Other features include a help area that explains medical words and symptom classification (e.g., respiratory, digestive).

4.3.2 Disease Correlation Engine

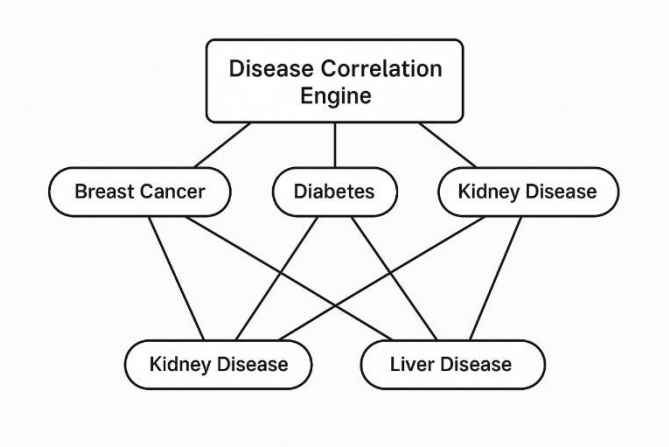
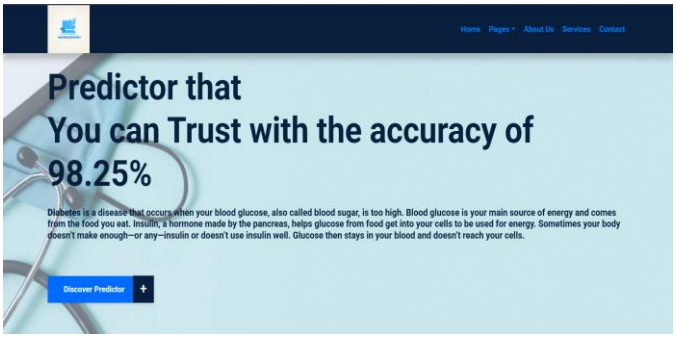
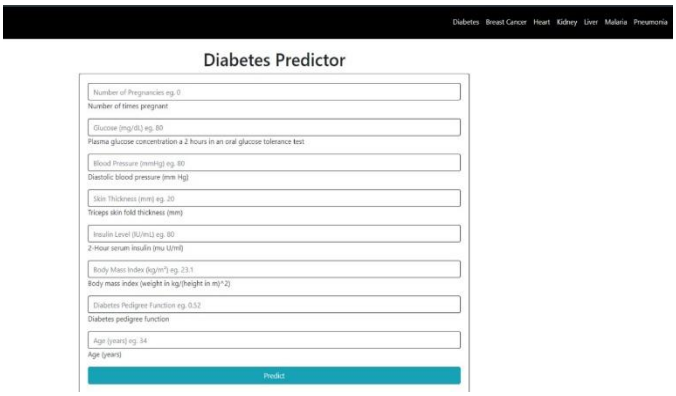


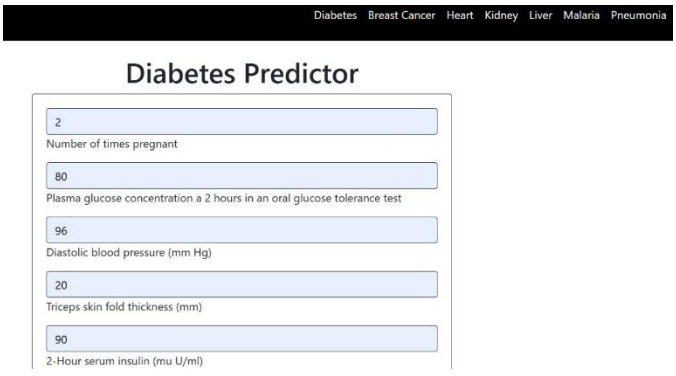
Figure 4.3.2.1: Visualization of a symptom-disease highlighting the correlation between common symptoms and multiple conditions.

A visual representation of the connections between various diseases using correlation analysis is provided by the "Disease Correlation Engine" figure. It starts with input data relating to five important diseases: Breast Cancer, Diabetes, Heart Disease, Kidney Disease, and Liver Disease. The central Disease Correlation Engine receives these illnesses and uses statistical techniques like Pearson or Spearman correlation to calculate their correlations. Based on patterns in patient data, the engine determines the degree to which each condition is related to the others. The findings are shown as a network, with lines indicating how strongly diseases are related to one another. By concentrating on diseases that frequently co-occur, this method aids researchers and physicians in understanding shared risk factors, forecasting disease development, and improving diagnosis techniques. It makes complicated medical data simpler.

5. RESULTS







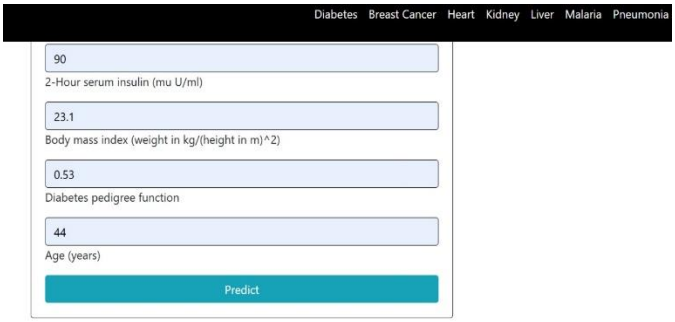


Figure 5.1: Results about a healthy person.

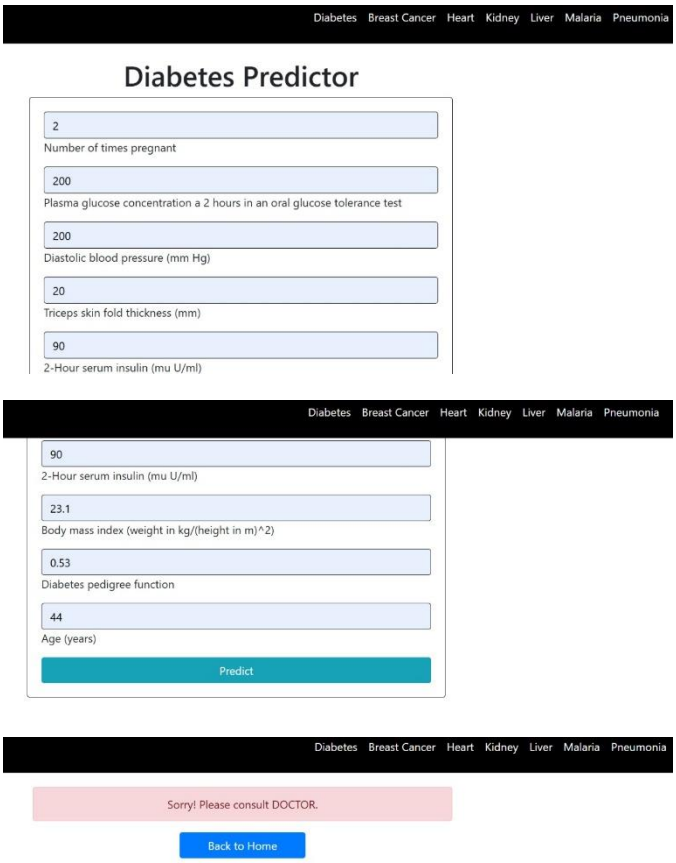


Figure 5.2: Results about disease affected person and suggesting to contact doctor .

The program is written in Python, and the following libraries are utilized extensively:

1. Pandas & NumPy - Scikit-learn - For preprocessing and data manipulation

2. Skirt line- For ML model implementation

3. Streamlit - For frontend development

4.Matplotlib/Seaborn -For model performance visualization

5.Joblib - For effectively saving and loading machine learning models

Lightweight and optimized for both local computers and cloud servers, the interface works well. It enables visual feedback on model output and real-time interaction with the trained models. Both dynamic model switching and user input logging are supported by the backend for future training enhancements. To guarantee safe platform usage, additional security features including input validation and session management have been added. For cross-platform compatibility, the deployment pipeline uses Docker-based containerization, and GitHub actions are set up for automatic deployment and testing. DVC (Data Version Control) is used to manage the version control of datasets and models, guaranteeing traceability and reproducibility.

We use 10-fold cross-validation to test and assess each model on the dataset. With an accuracy of more than 94%, the Random Forest Classifier yielded the best results out of all of them. To verify consistency and dependability, the system was tested by simulating various symptom combinations. Confusion matrix analysis and ROC curve visualization were also used in the evaluation to gauge classification performance. The precision-recall curves and F1 scores showed little overfitting, confirming that the model works effectively with unknown data. Students and medical professionals participated in user testing sessions to verify the application's usability, and they reported that the system was easy to use and educational. A monitoring dashboard contains usage logs and performance indicators for ongoing assessment, and alarms are set up to highlight unusual prediction behavior.

6. CONCLUSION

Machine learning's potential in healthcare diagnostics is demonstrated by the AI-powered medical diagnosis and disease support system. It offers a practical setting for initial symptom-based health evaluations. Although technology cannot take the role of medical professionals, it can help speed up diagnosis, raise awareness, and direct consumers to prompt medical advice. Personalized treatment recommendations, wearable device integration, and multilingual input support are possible future enhancements.

Additionally, the system might become even more useful in underprivileged and rural areas if it were expanded to include telemedicine and remote consultation capabilities. The increasing use of digital health technologies around the world puts this system in a good position to enhance human knowledge and expedite

diagnosis procedures. The platform can develop into a potent clinical decision support system that improves public and individual health outcomes by consistently learning from new data.

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