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Parkinson's Fall Detection System using Machine Learning and IoT

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***Abstract*—Parkinson's disease (PD) is a degenerative neurological condition characterized by numerous motor and non-motor aspects which may alter function in different ways. This overview summarizes the clinical symptoms of Parkinson's disease, with an emphasis on those features that distinguish the condition from other parkinsonian disorders. PD has historically been difficult to define, with doctors focusing on some symptoms while neglecting others, relying mostly on subjective rating scales. Voice can be utilized to detect and diagnose Parkinson's disease due to the disease's decline in motor control.With technological improvements and the abundance of audio collecting equipment in daily life, dependable models that can translate this audio data into a diagnostic tool for healthcare providers could potentially provide cheaper and more accurate diagnoses. This study investigates the efficacy of supervised classification methods, such as deep neural networks, in reliably diagnosing patients with the condition. Parkinson's disease (PD) is associated with an increased chance of falls, which can have serious repercussions for patients along with symptoms that are both motor and non-motor. A wearable fall-detection device has been offered as a solution to this problem. To detect patient falls, the system employs an accelerometer, an oximeter, and pressure sensors. A NodeMCU-ESP32 sends the gathered information to the cloud, enabling real-time communication and data analysis.In terms of fall detection sensitivity, specificity, and accuracy, this WFDS proved to be the best among available models. The fall detection method at the receiver end allows for accurate direction change in PD. Preliminary findings indicate that wearable fall-detection systems achieve high sensitivity, specificity, and accuracy in detecting the patient's fall.**

Keywords*—Fall detection, Elderly, Wearable sensor, Internet of Things, Support Vector Machine, NodeMCU-ESP32 , Machine Learning

I. Introduction

Parkinson's disease (PD) is a neuropathological ailment that impairs human motor activities. One of the most prevalent chronic neurological disorders, it primarily affects middle-aged and older individuals. According to estimates, there are over a million Americans who suffer with Parkinson's disease, with roughly sixty thousand new clinical diagnoses being made each year. PD has

historically been difficult to define, with doctors frequently focusing on specific symptoms and depending on subjective grading scales. However, the loss of motor function associated with Parkinson's disease opens the door to using voice as a diagnostic technique. Because of technological advancements and the proliferation of audio collecting equipment, it is now possible to construct trustworthy models that can translate voice data into accurate and cost-effective diagnoses. This study investigates the efficacy of employing supervised classification algorithms, such as deep neural networks, to identify Parkinson's disease with a peak accuracy of 85%, which exceeds the typical clinical diagnosis accuracy.

For those with Parkinson's disease, falls are a big issue, especially as they get older. Parkinson's disease affects around one million Americans, with 60,000 new instances being discovered annually. Falls can be devastating for patients, resulting in injuries, decreased quality of life, and even death. Parkinson's symptoms, such as tremors, muscle rigidity, gait impairment, and cognitive deficits, all bring about an increased risk of falling. Existing fall detection systems have shortcomings in terms of accuracy, identification of fall direction, and needless alarms. Unexpected falls become more prevalent and dangerous when the body's physical condition deteriorates with age. The necessity for an effective fall detection system is obvious in aging countries like Thailand, where a considerable percentage of the population seeks treatment in emergency departments owing to falls. Parkinson's disease is a significant contributor to falls worldwide, and it is expected to affect millions of people by 2030. Parkinson's sufferers have aberrant movements and several symptoms, including frequent falls, due to the depletion of dopamine-producing brain cells. Falls occur when dopamine synthesis drops by 75 to 80%, causing brain malfunction. Recurrent falls, with some patients falling multiple times per week, increase the risk of injuries including broken bones and can even lead to cardiac arrest or stroke. To address these issues, fall-detection systems provide a possible solution by minimizing the negative effects of falls, such as gait impairment, freezing of gait, slow movement, stumbling walking, depression, muscular tightness, limb pain, and visual and cognitive impairments. These technologies can assist avoid falls and minimize their consequences by giving early detection and notifications to carers and family members. The intention is to raise the general well-being and safety of people with Parkinson's disease while also reducing the burden on healthcare systems caused by falls.

II. Related Work

There have been other earlier studies conducted in the domain of elderly monitoring without the use of humans.Depending on the numerous kinds of sensors used, there are plenty of methods for monitoring fall detection.. The methodologies utilized can be broadly categorized into three categories: 1) wearable sensors; 2) vision-based approaches; and 3) acoustic, vibrational, and other ambience sensor-based approaches. An outline of the systems can be found below that use vision-based and non-vision sensors.

Wearable sensor-based approaches rely on accelerometer and gyroscope sensors worn by the patient. This device uses embedded sensors in wearables to detect patient mobility and position. Its ease of installation is one of this technology's advantages, low cost, and simple functioning. Disadvantages include the inability to identify many autumn events and the system's limited coverage area.

Ambient sensor-based approaches rely on gathering the subject's vibrational data, for instance, audio signals or shaking signals, which are created during autumn events. External sensors such as acoustic, infrared, vibrational, and pressure sensors are used in this system. These sensors can detect the nature of anything in their environment, and the accuracy of fall detection is directly impacted by the subject's distance from the sensor site. As a result, the system frequently generates false warnings. The primary drawback of this technology is that it does not cover all fall direction angles, the detecting area is restricted to around 12m, and the equipment is expensive.

A computer or a multiset of video cameras placed in the subject's body will be employed in a vision-based mechanism for detecting falls.

Yu et al. suggested a mechanism for detecting falls based on posture recognition in computer vision. For home surveillance, it relies on merely one camera. The disadvantage of this technology is the low detection rate, which stops the body from being tracked outside of the cameras' field of view, and the camera's exterior sensing will be pricey.

Huda Ali Hashim, Saleem Lateef Mohammed, and Sadik Kamel Gharghan developed a reliable technique for detecting falls for Parkinson's disease patients employing wireless sensor nodes and a data event algorithm. A sensor node for an accelerometer, a Myoware sensor node, and a receiver node make up the system. Because of its low power consumption, the wireless communication method employed was XBee S2C. Their completed work was lightweight, user-friendly, and compact. The Data Fall algorithm was presented in this study to identify the fall event direction without error. This has a major drawback. of this detection system is that the wireless communication technology, ZigBee, has a limited range inside constrained locations.

Ozcan, Koray, and colleagues proposed a wearable embedded smart camera for automatic detection of the falls and activity classification. The algorithm was developed using a CITRIC embedded camera. The Crossbow TelosB mote is majorly utilized for wireless data transmission. For activity classification, an optical approach is applied. Using the embedded camera system, the fall detection rate was 86%. The number of false positives (incorrectly generated fall alarms) caused by lying down events is increasing. The drawback of adopting this proposed method is that because the subject wears the camera, the surveillance will continue wherever the subject goes, therefore a wearable camera alleviates privacy problems. Using the embedded camera technology, the fall

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detection rate is 86.66%. The proper classification rates for sitting and lying down occurrences are 86.8% and 82.7%, respectively.

Patel, Shyamal, and colleagues presented a programme that makes use of wearable sensors to track fluctuations in patients. It was decided to make use of a support vector machine (SVM) classifier. SVM were compared to clinical scores derived from visual assessment of video recordings of patients performing a number of standardized motor activities such as tremor severity, dyskinesia, and bradykinesia. Seven trials were performed at 30-minute intervals, and data was gathered. Video recordings were made across each trial. The uniaxial accelerometer is located in the lower and upper limbs. The use of eight connected sensors in total did not aid in determining the direction of fall; this is the biggest disadvantage of this system.

Nooruddin, Sheikh, Md. Milson Islam, and Falguni Ahmed Sharna proposed an IOT-based device type invariant fall detection system. As long as they connect to the necessary modules, which include a tri-accelerometer, a buzzer, a Global System for mobile communication, a Global Positioning System, and Wi-Fi, smartphones, Raspberry Pi, Arduino, NodeMCU, and other devices can be used. The client-server architecture underlies the entire system. The server receives the accelerometer data from the devices, which is then sent to a machine learning model that examines the data to determine whether or not the fall actually happened. The system was 99.7% accurate, 96.3% sensitive, and 99.6% specific. One disadvantage of the recommended solution is that it necessitates compatible network connection between the client and server. Another drawback of the method that has been developed is that the client devices can only detect falls if they are placed in the left or right pant pocket. The entire dataset should be used to train the model. The client devices' protective cases should be used because the gadgets aren't usually watertight.

Hassan, Mohammad, Mehedi, and colleagues created a Smartphone-enabled fall detection system for the elderly. This paper describes a smartphone.

The next step is to choose a machine learning model that will be used to categorize the audio data as Parkinson's disease or not. Models that are comme-enabled automated detection method for recognition falls by analyzing data supplied by the smartphone's sensors. They created a hybrid deep learning model for online fall identification that was trained offline using the MobiAct public dataset. The outcomes of the tests showed that the suggested system is able to differentiate between falls and other events with greater precision. However, if the precision is not good, family members or carers will be alarmed mistakenly, resulting in a greater percentage of false alarms than genuine fall in detection.

Gia, Tuan Nguyen, and colleagues proposed a low-energy sensor node for an IoT-based fall detection system. Wearable sensor nodes, a gateway, and a black-end system comprise the system architecture. The sensor node system collected and transmitted data to a smart gateway using a wireless communication protocol. Because this work is primarily concerned with energy efficiency, the energy consumption of wearable sensor nodes in various circumstances was evaluated in order to find ideal strategies for enhancing energy efficiency. The hardware and software aspects or strategies influencing the sensor node's lifetime are explored. Wearable gadget comparison with various devices offered by others. Experiment results show that the sensor node utilized can function for 76 hours with a 1000mAh battery in harsh conditions.

M. Shahidul Islam et al. published "A Smartphone-Based Fall Detection System for Parkinson's Disease Patients Using Machine Learning Techniques" This paper offers a fall detection system that detects falls in Parkinson's disease patients using smartphone sensors and machine learning algorithms.

S. Y. Seo et al. published "A Machine Learning Approach for Fall Detection in Parkinson's Disease Patients Using Inertial Sensors" A machine learning approach was employed in this study to detect falls in Parkinson's disease patients using data from inertial sensors.

III. Proposed Methodology

The following methods can be applied to build a Parkinson's disease detection model utilizing voice data:

A. *Collect data*

The first stage in developing a Parkinson's disease detection algorithm is gathering a large dataset of speech recordings from people with and without Parkinson's disease. In terms of age, gender, and ethnicity, the dataset should be diverse.

B. *Prepare the data*

The data is pre-processed by converting the audio recordings to digital format, reducing any noise or background sounds, and breaking the audio into smaller parts.

C. *Extraction of Characteristics*

The following stage will be to extract features from the audio data. The qualities of the audio that will be utilized to train the model are referred to as features. Pitch, loudness, formants, jitter, and shimmer are all prominent features utilized in voice analysis.

D. *Label the Data*

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After the features have been retrieved, the data must be labeled as Parkinson's disease or non-Parkinson's disease. This entails determining which samples are from people with Parkinson's disease and which are not using medical records or other diagnostic procedures.

E. Model Selection

The next step is to choose a machine learning model that will be used to categorize the audio data as Parkinson's disease or not. Models that are commonly used include logistic regression, decision trees, and neural networks.

F. Model Training and Testing

A supervised learning strategy is used to train the chosen model on the labeled data. The accuracy of the model is next tested using a distinct set of labeled data.

G. Fine-tune the Model

The model's performance can be improved by fine-tuning it based on the accuracy results.

H. Deploy the Model

After fine-tuning the model, it can be used to detect Parkinson's disease in new voice recordings.

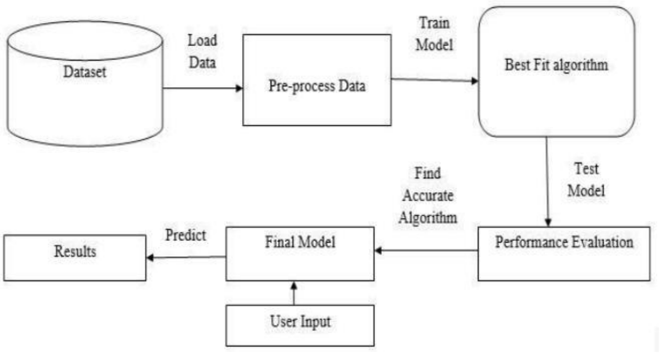

Fig. 1. Data Flow Diagram for the proposed ML model

Fall detection technology, which can interact wirelessly and consists of ESP32, Buzzer, OLED, Max30100, Bmp180, Accelerometer sensor (ADXL337), and GPS (Global Positioning System) neo6m, is the methodology we developed. The accelerometer sensor (ADXL337) is the system's key component. The ESP32 microcontroller, which includes built-in Wi-Fi, is used.

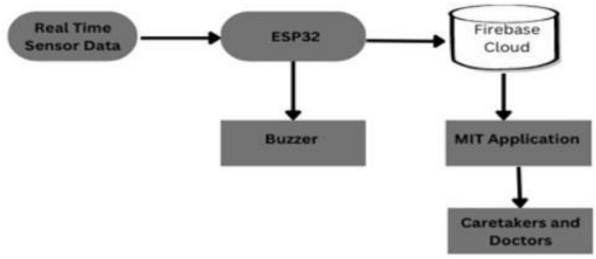

Fig. 2. Data Flow Diagram for the proposed IoT model

A. Accelerometer Sensing element Node

The new model incorporates a tilt sensor. Different inclination angles are taken into account for different fall angles. They are referred to as "fall-angles" because only at these fall angles do the tilt switches charge and send energy to the accelerometer sensor node's components. The ADXL337 accelerometer measures the acceleration in three axes (x, y, and z) over a full-scale range of 3g and has a sensitivity of 300mV/g. AdXL337's sampling rate is set to 24Hz/s.

B. System architecture and design

Many wearable sensors have been created for the WFDS in the medical field. As a result, these developments provide more opportunities to assist carers in protecting their seniors by enhancing the output of the wearable sensor by utilizing ESP32 for the fall detection system. An accelerometer node and a receiver node make up the system. The MAX30100 is used to implement the oximeter sensor, which detects the pulse and oxygen saturation levels in the patient's blood.The buzzer acts as an alarm to notify carers of the presence of a fallen patient, check the data signal, and make a patient-related medical diagnosis.. The choice is displayed via OLED. The sensor board and the monitoring system are the two key components of the proposed system. The sensor-board, or fall detecting device, is the initial component. It is made up of an accelerometer sensor, as well as the ESP32.ADXL337 triaxial accelerometer with three-axis magnetic field. It detects the kinematic signal from the patient's daily activities. The ESP32 is utilized as a coordinator to communicate the observed kinematic signal to Firebase Cloud.The system's fall detection method is depicted in the flowchart. This method creates three triggers for gathering events that occur throughout the system's operation. The first trigger determines the human movement angle, while the subsequent triggers decide the amplitude of the accelerated movement. The Firebase platform serves as the backend for developing Android, web, and iOS applications. It includes a real-time database, numerous APIs, numerous

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authentication methods, and a hosting platform. It can power the backend of the app, such as user authentication, data storage, and static hosting. It creates cross-platform native mobile and web apps using IOS, Android, and the JavaScript SDK.

Fig. 3. Fall Detection System using ESP32 and sensors

In this case, ESP32 is a microcontroller that calculates fall detection with danger level assessment by comparing it to threshold values. The ESP32 is a device developed for IoT and embedded systems. The key reasons for using ESP32 in the needed prototype are its low cost, low power, and Wi-Fi capabilities. The real-time data analysis and data storage system, which is utilized to record the kinematic signal to Cloud storage, is the second key component. This component serves solely as a controller. It comprises Firebase Cloud, which serves as real-time storage and aids in the creation of a prototype, growing the IoT-based project, and data management using cloud computing technologies. The Firebase Cloud platform is utilized here to process the kinematic signal received from the ESP32. The data is monitored and graphed by Firebase Cloud. As a result, the fall detection data will be transmitted to the web server. The respective hospital or carers can independently check the data signal and diagnose medical information related to fall episodes.

C. *Firebase Cloud Storage*

The Firebase platform serves as the backend for developing Android, web, and iOS applications. It includes a real-time database, numerous APIs, numerous authentication methods, and a hosting platform. It can power the backend of the app, such as user authentication, data storage, and static hosting. With IOS, Android, and JavaScript SDKs, it creates cross-platform native mobile and online apps. It also uses server-side libraries or REST API authentication to link Firebase to the existing backend. Users can employ anonymous passwords, or various social authentication methods. The benefits are as follows: It is simple to use and user friendly. Because data is real-time, any change is instantaneously updated to all connected clients. Firebase Cloud always provides a straightforward control panel.

D. *Firebase Cloud Platform*

Firebase is a backend platform for developing Web, Android, and iOS apps. It provides a real-time database, several APIs, various authentication types, and a hosting platform. The backend of an app can be powered by Firebase, which includes data storage, user authentication, and static hosting. With the Android, iOS, and JavaScript SDKs, you can create cross-platform native mobile and online apps. It also uses server-side libraries or REST API to link Firebase to the existing backend. Firebase's features include that Firebase supports JSON data and all users that are connected to it receive real time updates following every change. Authentication - We can employ anonymous authentication, passwords, or various social authentications. The following are the benefits of Firebase: It is straightforward and easy to use. There is no need for complex configuration. Because the data is real-time, any changes will automatically update connected clients. Firebase provides a straightforward control panel.

E. *Fall Detection Algorithm*

The fall detection approach in the system is classified into two types: machine learning-based and threshold-based. A machine learning-based technique is used to distinguish an actual autumn event from usual activity. The threshold computes the total acceleration as well as the rotation angle value. The obtained findings are compared to the thresholds established using the given data.

As a result, effective threshold values are provided by the multidimensional fall detection technique.

The system's fall detection method is illustrated as a flowchart in the below Fig . This method generates three triggers for gathering events that occur during system operation. The first trigger is used to calculate the angle of human movement, and additional triggers are used to determine the angle of human movement.

The fall detection method of the system is depicted in the flowchart below. This method creates three triggers for gathering events that occur throughout the system's operation. The first trigger determines the human movement angle, while the subsequent triggers decide the amplitude of the accelerated movement.

The SVM approach is used to compute the magnitude of the acceleration.

$$= (\quad ^2 + \quad ^2 + \quad h^2)^{1/2}$$

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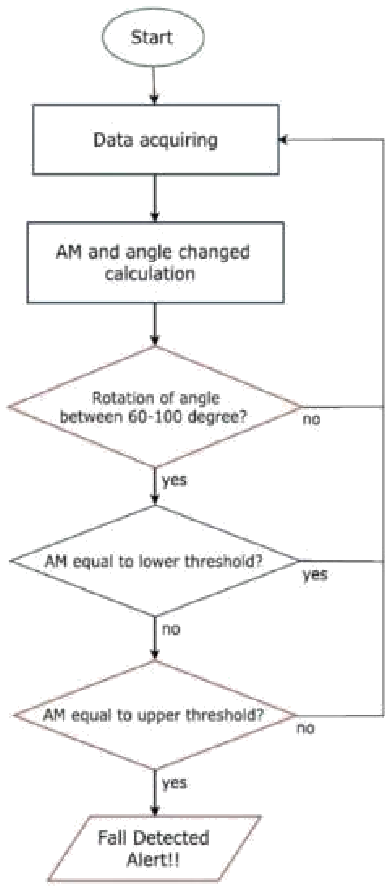

Fig. 4. Flow Chart depicting IoT logic

The Roll is the x-axis angle rotation that specifies the human body's sideslip angle to the right and left. The pitch represents the angle of rotation around the y axis, which depicts the body's forward and backward movements; the heading indicates the angle of rotation around the z-axis, which depicts the human body's right and left corners.

The rotational angle, often known as angular kinematics, is given by the equation as-

$\cdot \quad = | \; || \; | \quad \theta$

The arranged angle is calculated as illustrated below-

$\theta = ^{-1} \quad | \quad \cdot \; | \; || \; |$

Where a(ax, ay, az) is the device's rapid value, b(bx, by, bz) is the elderly's reference position while using the device vertically, and is the angle rotation between a and b.Once the accelerated magnitude (AM) value is obtained, the system will calculate the rotation of the angle altered value. To check the fall detection result, the fall detection algorithm compares the generated results to the predefined degree of rotation angle and threshold values.If the degree of rotation angle is more than 60 - 100, the body has lost its balance, resulting in an unintended fall. In this algorithm, the predicted AM value will be compared to a predefined threshold value.

If the computed accelerated magnitude exceeds the lower threshold, the algorithm will activate trigger 1 to indicate that no fall event was identified because the danger of a fall is too low, or because the elderly are engaged in activities that are unlikely to result in a fall. The procedure will be triggered if the calculated accelerated magnitude exceeds the upper threshold, indicating the presence of a fall event. It demonstrates that a genuine autumn occurrence occurred. It will then send a notification to the carer informing them that a rescue is needed.It demonstrates that a genuine autumn occurrence occurred. It will then send a notification to the carer informing them that a rescue is needed.

F. *Sensors*

The first two bytes contain IR data, whereas the next two bytes contain RED measurements. The FIFO buffer cannot be accessed with I2 C since it points to the same address as the FIFO.

The first two bytes yield IR measurements, while the following two bytes yield RED measurements. Because the FIFO points to the same address, the FIFO cannot be read with I2 C. We must finish the transaction in order for the FIFO output address to hold the next values. The MAX30100 includes a 50/60Hz filter.If we are only expecting to detect a pulse, we only need IR. To achieve oxygen saturation, we'll need to turn on both IR and RED LEDs. By altering the sampling rate and pulse width of the LEDs, we can change the ADC resolution. The pulse width and sampling rate must be tightly linked.

G. *Buzzer and it's working*

By altering the sampling rate and pulse width of the LEDs, we can change the ADC resolution. The pulse width and sampling rate must be tightly linked.Because the screw is in touch with the vibrator arm, current continues to flow into the coil. After exiting the coil, it strips through the closed code key and returns to the battery.

A magnetic field forms around the iron bolt as currents flow through the electric pencil. When the bolt changes into an electromagnet, it attracts the vibrator arm.The circuit will be opened as the arm begins to swing towards the bolt. As a result, the current runs out. The magnetic field diminishes as a result, allowing the vibrator arm to return to its original position against the contactor. Now that the circuit has been rejoined, current begins to flow again, and the cycle begins again. Regardless of how quickly we push and release the code key, the current will swing hundreds of times between the circuits. A buzzer sound is produced as a result of the rapid movement of the vibrator arm.It's fascinating not only to create the code set, but also to use it, especially with a partner. There is no need to create two identical sets of buzzers and code keys so that carers and patients may communicate.

To assess the usefulness of the proposed fall detection system, classification models should be tested on datasets collected from elderly and young people. In this experiment, 14 people ranging in age from young to elderly participate in a series of test cases relevant to realistic scenarios.

IV. Conclusion

Disease diagnosis and prediction can be accomplished using non-invasive vocal biomarkers as features in automated machine learning frameworks. Our research examines the performance of various machine learning classifiers in identifying diseases using noisy and high-dimensional data. We can attain clinical-level accuracy with proper feature selection. These findings are interesting because they provide new methods for assessing patient health and neurological disorders using speech data. The excellent accuracy of models utilizing brief audio samples shows that adopting denser feature sets, such as spoken word or video, may improve disease prediction and clinical validation in the future.

To summarize, creating a Parkinson's disease detection model using voice data entails gathering a diverse dataset of audio recordings, preprocessing the data, extracting features, labeling the data, selecting a machine learning model, training and testing the model, fine-tuning it based on results, and deploying it for use. While this model has the potential to aid in the early identification and treatment of Parkinson's disease, it is important to note that it should not be used in place of medical diagnosis or advice from trained healthcare professionals.

Our project's goal was to develop an intelligent gadget for fall detection for Parkinson's sufferers using the IoT framework, and we succeeded with our suggested solution. The ESP32 offered real-time monitoring via the Firebase cloud, while an accelerometer sensor (ADXL335) detected the varied directions of patient falls. The model was tested with sensor values from different circumstances and patients, and the best accurate model for fall prediction was chosen. In comparison to other existing systems, our method demonstrated roughly 82.5% accuracy and 95% specificity. The data that has been uploaded to the Firebase server can be used for medical research. Our system's real-time position updates and fall direction are critical features that allow carers and family members to respond quickly. We intend to expand testing with more patients in order to enhance prediction results even further.

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