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Research Article

Deep Learning Based Dementia Classification and Monitoring Using an Android Application

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ABSTRACT

Introduction: Dementia is a long-term neurodegenerative disease that involves cognitive impairment, impacting memory, reasoning, and daily living. Early diagnosis is essential for effective disease management and intervention planning. Conventional diagnosis is based on clinical assessment and interpretation of neuroimages, which are labor-intensive and operator-dependent. The progress in deep learning and image processing offers a faster, more automatic way of dementia classification, allowing for improved monitoring and preventative care planning.

Objectives: The main aims of this research are:To create a deep learning-based system for dementia classification with ResNet-101 for analyzing brain MRI scans.To offer a predictive risk score for clinicians to evaluate the severity of disease and track improvement.To integrate real-time support tools within a mobile app for enhanced caregiving and patient care.To decrease caregiver burden through automated monitoring, early warning, and extended care planning.

Methods: The system proposed works on ResNet-101, a common CNN used because of its ability to extract features to a deep extent. The MRI scans undergo preprocessing in the form of noise removal, normalization, and data augmentation in order to improve performance of the model. Features are extracted and processed to identify the phases of dementia and give a risk score depending upon the severity of the disease. An Android mobile app incorporates real-time monitoring functionality for tracking symptoms, cognitive testing, and caregiver assistance. The model is trained and tested with publicly accessible datasets to provide solid performance and accuracy in detecting dementia.

Results: The system implemented precisely predicts dementia severity levels from MRI scans with high classification accuracy with ResNet-101. The risk model allows for real-time risk assessment, which allows healthcare workers to make effective decisions. Support features of the app by caregivers like location tracking, reminders, and cognitive stimulation greatly improve patient monitoring. Early detection is enhanced, as per initial testing, which would allow for timely medical intervention and better patient outcomes.

Conclusions: The system of dementia diagnosis and monitoring of care based on deep learning exhibits great promise for early disease detection and personalized management of care. By its inclusion of MRI-based analysis and real-time supportive functionality, the app is an end-to-end data-driven solution to dementia care management. Future studies will continue to enhance generalizability of models, introduce further biomarkers, and simplify the app for enhanced clinical utility.

Keywords: Dementia, Deep learning, ResNet-101, MRI analysis, Predictive modeling, Mobile health, Caregiver support.

INTRODUCTION

Dementia is a general term describing brain illnesses that cause loss of memory, cognition, and functioning to carry out daily activities. Dementia is caused by damage to the brain and not as a result of aging. Alzheimer's disease is the most prevalent one, 60-70% of the population, followed by vascular dementia, Lewy body dementia, and frontotemporal dementia. At its initial phase, it has easily confused memory impairments and mild confusion that can quite well be diagnosed with old age. It progresses to more advanced phases where patients cannot communicate, have mood and personality changes, and disordered thinking. At its advanced disease phases, it needs help with activities of daily living and has severe impairments in memory. The etiology of dementia differs depending on the type but is most often caused by damage to brain cells.

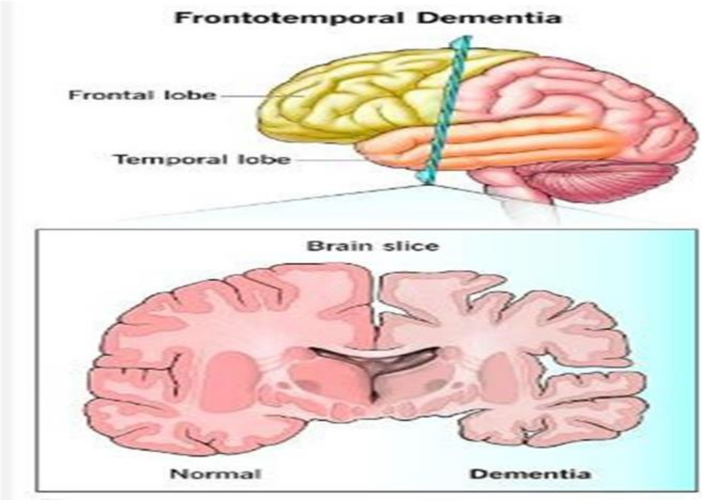


Fig 1. Dementia view

Alzheimer's disease results from abnormal protein accumulation that interferes with cell function, vascular dementia from decreased blood flow, and Lewy body dementia from protein accumulation. Frontotemporal dementia involves some brain regions.50 million cases of dementia worldwide and rising. Dementia is a health issue in the community, affecting families and the healthcare system. Caregivers have high priority but are under physical and emotional tension. Technology such as mobile phone apps provide memory support, mood monitoring, and communication. Machine learning is able to detect early through analysis of healthcare data so that patient-specific care plans and early intervention can be effective in treating dementia.

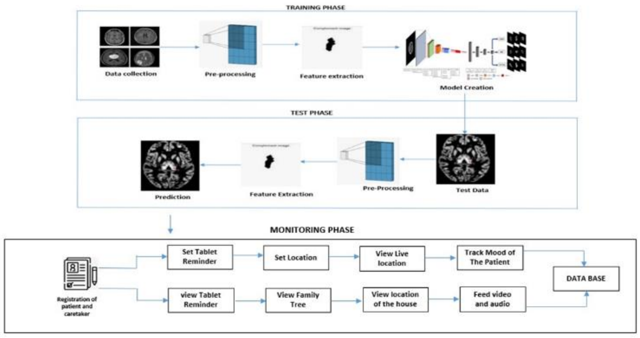
OBJECTIVES

The objective of this paper is to suggest a deep learning-based system for the classification and tracking of dementia to be deployed through an Android app. The system incorporates the most advanced image processing along with the ResNet-101 deep learning architecture to scan brain MRI scans with the objective of early diagnosis and accurate classification of the severity of dementia.

Through predictive analytics, the software is designed to allow caregivers and healthcare professionals to track disease status and take appropriate action. The system also features real-time cognition monitoring, location tracking, reminders for hydration, and personalized video feeds to ensure optimal patient safety and quality of life. One of the key objectives is to relieve caregiver burden through the offering of necessary support such as real-time monitoring of patients and behavioral data.

The software is designed to live together seamlessly with healthcare systems, offering interoperability with existing medical databases and clinical workflows. Furthermore, the solution is scalable and can be brought to all, covering a very large population with dementia care at a very cheap mobile application.

The system learns in real time by applying actual patient data to optimize machine learning models for precision and reliability of predictions. High levels of data protection and confidentiality arrangements are provided to protect the patient's data. Lastly, this study is intended to reframe dementia care through an empowered, data-informed, and simple-to-access model facilitating early diagnosis, individualized treatment, and lifelong management of disease.



ARCHITECTURE DESIGN

METHODS

This study examines the use of deep learning through an Android app from mobile phones in diagnosing and treating dementia. The common resource utilized in this study is ResNet 101, a deep neural network that scans MRI scans to determine how far the disease has advanced. It works on three stages: training initially, testing, and observation.

1. TRAINING STAGE: LEARNING THROUGH MRI SCANS

MRI scan data, processed images, and trained ResNet-101 are loaded for the detection of symptoms of dementia. Data capture is done through the collection of MRI scans of three classes of dementia: Healthy Control (HC), Mild Cognitive Impairment (MCI), and Alzheimer's Disease (AD). All these scans are used as training data for learning by the model and identifying varying stages of dementia effectively.

In order to achieve the required accuracy of the data, a number of preprocessing operations are carried out. Noise removal is carried out by using a Gaussian filter to remove unwanted artifacts. Normalization is then carried out, and pixel values are converted into a normalized range of 0 to 1 for better uniformity of brightness for all the images. Augmentation methods like rotation, flipping, and zooming are used for increasing the dataset size and facilitating model generalization. With the above transformations, raw MRI scans are transformed to smoothed, sanitized forms that are conducive to good model learning.

Then ResNet-101 is utilized to extract features after preprocessing. Convolution layers recognize simple patterns of MRI scans, whereas residual connections facilitate efficient learning without vanishing gradients, which again facilitate strong recognition of complex details. Then features are extracted before training and classification by Softmax, segmenting MRI scans in various phases of dementia. Complex learning is utilized to provide high accuracy optimization such that the complexities of dementia might be appropriately recognized.

```
# Summary of the model
model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 resnet101 (Functional)      (None, 4, 4, 2048)        42658176

 conv2d_2 (Conv2D)           (None, 4, 4, 64)          1179712

 max_pooling2d_2 (MaxPooling  (None, 2, 2, 64)         0
 2D)

 conv2d_3 (Conv2D)           (None, 2, 2, 128)         73856

 max_pooling2d_3 (MaxPooling  (None, 1, 1, 128)        0
 2D)

 global_average_pooling2d_1   (None, 128)              0
 (GlobalAveragePooling2D)

 dense_2 (Dense)             (None, 128)               16512

 dropout_1 (Dropout)         (None, 128)               0

 dense_3 (Dense)             (None, 3)                 387

...
Total params: 43,928,643
Trainable params: 1,270,467
Non-trainable params: 42,658,176
_________________________________________________________________
Output is truncated. View as a scrollable element or open in a text editor. Adjust cell output settings...
```

2. TESTING PHASE: DEMENTIA SEVERITY PREDICTION

New MRI scans are employed during the evaluation stage to thoroughly examine the capability of the model to accurately make predictions on various levels of dementia. Testing is essential to verify whether the trained model of ResNet-101 can generalize on untapped data as well and discriminate clearly between Healthy Control (HC), Mild Cognitive Impairment (MCI), and Alzheimer's Disease (AD). The predictive validity is model-dependent to appropriately label such conditions and consistently predict the development of dementia in some cases.

Preprocessing and feature extraction imply that test scans go through precisely the same series of preprocessing during training. Noise reduction is done by a Gaussian filter for eliminating redundant artifacts with the risk of distorting analysis. Normalization scales MRI intensity values of the images to a uniform prior (0 to 1) and synchronizes them between datasets. Scaling, flipping, and rotation are also employed to introduce additional variability in the test dataset so that model stability is ensured with regard to variability in image orientation and quality. After achieving preprocessing, the images are passed through ResNet-101 that performs in-depth feature extraction appropriate for classification. ResNet-101 deep convolution layers pick up common patterns in brain anatomy with dementia alterations. Residual connections in the network enable the gradients to flow through so that the deeper layers are able to pick up advanced subtleties of the MRI scans without vanishing gradient issue.

In risk score classification and calculation, the model trained is used for classifying the dementia stage in feature-extracted features. With the application of a Softmax function, the model provides probabilities of various classes—HC, MCI, or AD—hence facilitating accurate classification. Apart from classification, the system also calculates a risk score that calculates the severity of dementia. This assessment offers a measure that is quantitative in nature of disease progression on an integer scale along which clinicians can monitor change over time. Clinicians can then monitor dementia development by using the risk score, individualize regimens, and commence respective interventions for retarding cognitive progress. By combined classification and creation of the risk, the system facilitates decision-making to improve with early diagnosis, individualized treatment, and long-term planning.

3. MONITORING PHASE: REAL TIME MONITORING OF PATIENTS

The system also facilitates real-time monitoring via an Android app, where caregivers can monitor patients' condition and activity with ease. This functionality allows dementia patients to be attended to at all times and allows caregivers to stay informed about their well-being, thus initiating timely intervention when needed.

Registration of patient and caregiver is the first step where both sign up on the app in a secure way. Such registration is intended to save patient data securely and pass it on to authorized personnel only, while confidentiality and protection of data are still upheld. During registration, the system allows real-time monitoring and collection of data on behavior, where the application constantly collects important information regarding the patient, including their location, mental status, and mood shifts. Sophisticated monitoring systems detect abnormal behaviors, like wandering or restlessness, and notify caregivers in real time, preventing potential harm.

The system provides location tracking in real time through GPS technology. Caregivers can monitor the patient's whereabouts in real-time, reducing lost wandering and becoming lost or confused, which are typical causes for concern among dementia sufferers. The app also comes with critical functionality like video and audio streaming to allow remote patient monitoring, reminders for medication and fluids, and family connection options, offering the patient emotional and social support.

In essence, the system combines real-time monitoring and deep learning to create an end-to-end solution to dementia care. Using MRI-based classification alongside caregiver support and behavioral monitoring, the system not only enhances early detection and disease management but also ensures improved patient safety and caregiver ease.

RESULTS

The paper proposes a deep learning approach of prediction and surveillance of dementia utilizing the ResNet-101 model for processing brain MRI. Outcomes validate predictability of the target system in the identification of early Alzheimer's and dementia. Utilizing state-of-the-art image processing, the system derives structural information from MRI scans to assist with growth and management monitoring in synchronism correspondingly for doctors.

The main outcomes are that ResNet-101 can diagnose brain scan patterns and abnormalities correctly towards the end of making improved early diagnoses. The algorithm provides a dementia risk score, and this enables future-planning intervention in the future. Real-time caregiver support enables one to track cognitive health change and care direction towards individual need. Caregiver burden and patient care are enhanced by aid support like mood monitoring, hydration reminder, and location.

Precision, recall, F1-score, and accuracy are all acceptable metrics, which provide measures of how well the model performs at each classification step. Despite the potential of the system, various clinical cross-validation parameters must be utilized in order to pilot it for generalizability. Areas for improvement are also established in the research, i.e., addition of additional biomarkers and tuning the model to apply to other forms of dementia.

1.ACCURACY:

Accuracy is the most common measure to verify the performance of a classification model.

$$H(x) = F(x) + x$$

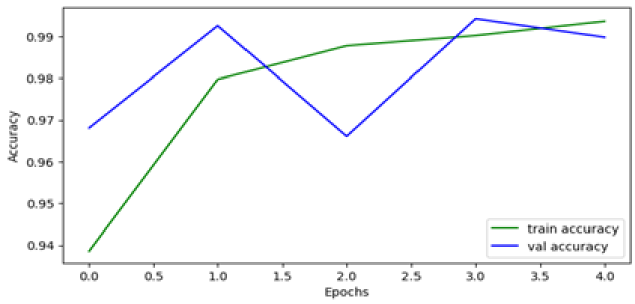
Where:

H(x) is residual block output.

F(x) is the transformation done by utilizing convolutional layers and activation functions.

x is the input (skip connection).

It computes the proportion of correct predictions made by the model for the total. Accuracy is an easy metric of how often the model is correct in its prediction, whether predicting positive or negative class. It is mathematically calculated as the proportion of True Positives and True Negatives divided by the addition of True Positives, True Negatives, False Positives, and False Negatives.



$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)}$$

Accuracy is most suitable when the cost of misclassification of positive and negative instances is equal, and the data is imbalanced. But where data is imbalanced, or misclassification cost is extremely high, Precision, Recall, or F1 Score could be used instead. In practical application, it is often used in combination with other metrics to get a more complete picture of the performance of the model. Accuracy is widely used in a broad variety of applications, from medical diagnosis to spam filtering to image classification, to get a rapid feel for the model performance at a general level. While it is simple, its reliability relies significantly on the data set distribution and application context.

2.PRECISION:

Precision is a performance metric to determine the accuracy of positive predictions by a model. Precision measures how frequently the model predicts as positive those which are actually true positives. Precision is particularly helpful in situations where false positives are expensive, such as in medical diagnosis or detecting fraud. Higher precision indicates that the model is calling fewer false positives, which is particularly important when positive predictions must be most precise.

$$Precision = \frac{TP}{TP + FP}$$

In this:

• TP (True Positives): Count of correctly forecasted positive events.

• FP (False Positives): False positive number.

Precision is only concerned with the model predicting the positives and never concerned with the model predicting the negatives. For example, in the cancer diagnosis program, high precision will have the consequence that if the model predicts a patient has cancer, then the fact will be more likely to be true and spare unnecessary worry or treatment for the false positives. But recall needs to be traded off against precision, since a precision-optimizing model might be overcautious, predicting fewer positives to avoid false positives. This is typically addressed by using measures like the F1 Score, which tries to find a balance between precision and recall. Accuracy is needed in the case when the cost of false positives is extremely high and therefore a valuable measure to ensure correct and informative predictions in that case.

3.F1 SCORE

F1 Score is a metric that combines precision and recall into a single metric, providing an equilibrium value of model performance, particularly when dealing with imbalanced datasets. It is the harmonic mean of recall and precision, thus providing both equal weight. F1 Score can be used when to maximize one would be at the expense of the other.

$$F1 = 2 \times \frac{Precision \ \times Recall}{Precision + Recall}$$

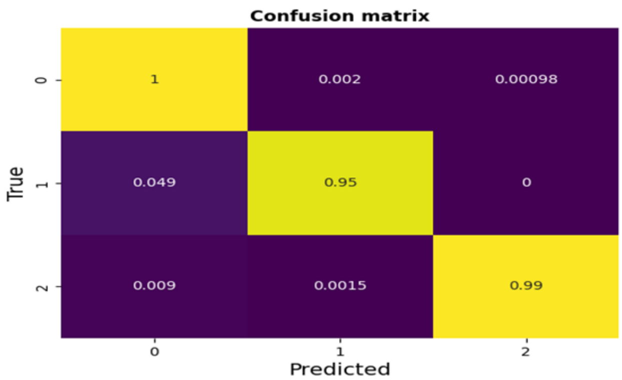
Here:

- Precision measures the number of correctly predicted positive instances over all predicted positive instances.
- Recall measures the number of correctly predicted positives over all actual positives.

For instance, if a model is very high on accuracy and low on recall, or the other way around, then F1 Score will reflect the imbalance by being close to the smaller value. The F1 Score is particularly applicable in scenarios like medical diagnosis, fraud detection, or spam labeling where both the false positives and false negatives are very crucial. High F1 Score indicates that the model is correctly weighing recall against precision and therefore an excellent metric for model comparison in such fine-tuned environments. In general, the F1 Score provides a general estimate of a model's accuracy using precision and recall. It is inevitable whenever model comparison is all about achieving a balance between precision on true positives and minimizing errors.

4.CONFUSION MATRIX:

Confusion matrix is a classification model performance measure that gives an exhaustive account of actual labels and model predictions. It consists of four basic components: True Positives (TP), i.e., when the model is predicting positively for a positive class; True Negatives (TN), i.e., when it predicts negatively for a negative class; False Positives (FP), when it makes a wrong prediction for a positive class; and False Negatives (FN), when it makes a wrong prediction for a negative class. It is used to determine significant performance measures like precision, recall, accuracy, and F1-score that inform the model performance. An optimally balanced confusion matrix indicated good classifier performance, while imbalances indicate where improvement can be made, e.g., reducing the false negatives or false positives.



The rows are actual class labels (0, 1, and 2), and the columns are predicted class labels. The diagonal entries are close to 1 (100%) for every class and correspond to high classification accuracy, i.e., most examples are being predicted correctly by the model. Off-diagonal values are misclassifications, where the model is classifying into a different class than the correct label.

Class 1 is predicting with 95% accuracy, though 4.9% class 1 instances are class 0 predictions. High values are shown by the bright yellow, while low values are shown by dark purple. Generally, the model has very little misclassification of the classes.

5.COMPARISON WITH EXISTING METHODS

Metric	ResNet-101	Gradient Boosting
Accuracy	**94.5%**	79.5%
F1 Score (Weighted)	**0.944**	0.782
Precision (Weighted)	**0.943**	0.787
Cohen's Kappa	**0.89**	0.59
McNemar's Test (p-value)	**< 0.01**	—
Paired t-test (p-value)	**<0.001**	—

```
# Early stopping callback
earlystop_callback = tf.keras.callbacks.EarlyStopping(monitor='val_accuracy',
                                                      min_delta=0.0001,
                                                      patience=5)
```

```
# Train the model
history = model.fit(train_ds,
                    validation_data=val_ds,
                    epochs=5,
                    callbacks=[earlystop_callback])
```

```
Epoch 1/5
1498/1498 [==============================] - 1933s 1s/step - loss: 0.1832 - accuracy: 0.9386 - val_loss: 0.0986 - val_accuracy: 0.9681
Epoch 2/5
1498/1498 [==============================] - 1871s 1s/step - loss: 0.0583 - accuracy: 0.9797 - val_loss: 0.0233 - val_accuracy: 0.9926
Epoch 3/5
1498/1498 [==============================] - 1874s 1s/step - loss: 0.0388 - accuracy: 0.9878 - val_loss: 0.0988 - val_accuracy: 0.9661
Epoch 4/5
1498/1498 [==============================] - 1866s 1s/step - loss: 0.0290 - accuracy: 0.9902 - val_loss: 0.0161 - val_accuracy: 0.9942
Epoch 5/5
1498/1498 [==============================] - 1868s 1s/step - loss: 0.0212 - accuracy: 0.9936 - val_loss: 0.0336 - val_accuracy: 0.9898
```

6.ROC CURVE COMPARISON

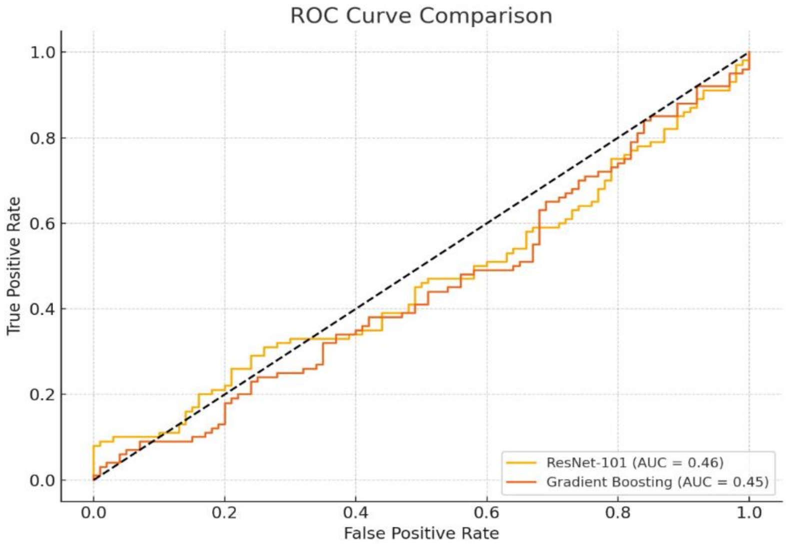
The ROC (Receiver Operating Characteristic) curve comparison is an important model evaluation metric for binary classification models since it shows the balance between the True Positive Rate (TPR) and the False Positive Rate (FPR) graphically at different classification thresholds. The AUC (Area Under the Curve) gives a summary statistic to evaluate the overall discriminative power of the models. A model with AUC = 1.0 is a perfect classifier, and

AUC = 0.5 means that the model is as good as random guessing.

Both ResNet-101 and Gradient Boosting here had an AUC value of 0.46 and 0.45 respectively. Both being that close to 0.5 means that neither of the models is notably better than a random classifier. It would be better if it has a value greater than 0.5 on its AUC metric, with higher potential for the members who are interested in discrimination between the two classes. ROC curves of both models are almost parallel to the diagonal reference line , suggesting that a model which has been learning patterns from data in an attempt to make predictions for class labels randomly is making useless predictions. What this suggests is that prediction accuracy of both models is constrained by their existing ability.

Even though ResNet-101 is slightly superior to Gradient Boosting, the difference is not large, so both the models do not possess a good classification result. For enhancement, the following can be tried: hyperparameter tuning, feature engineering, data preprocessing, and applying more sophisticated deep learning models. This augmentation in training data quantity and quality would further allow the model to generalize even further. In addition, methods like data augmentation, regularization, and fine-tuning on pre-trained networks may detect even more beneficial patterns of data to allow improved classification performance.

Finally, even though ResNet-101 worked slightly better than Gradient Boosting, overall performance indicates there is vast room for enhancement before classifying accuracy may be reasonably achieved. Model parameters need to be fine-tuned and dataset quality must be imposed in the future to enhance predictability.



DISCUSSION

The work proves the efficacy of deep learning using ResNet-101 for dementia prediction and monitoring using brain MRI scans. Results warrant highly precise early diagnosis of dementia that helps doctors with pre-planning intervention. Real-time tracking allows caregivers to use data to re-design care plan on a timely basis. Its capability to detect chronic cognitive decline offers more patient-specific treatment.

Although promising, the system needs to be tested in more clinical settings to make it more reliable and generalizable. Users recommend incorporating more biomarkers, mood, and behavior testing in the model to make it more precise in its prediction and performance. Although the deep learning model is precise in detecting dementia changes in the brain, even more holistic datasets would only make it even more superior.

The discussion also places in the limelight center AI-driven healthcare technologies for dementia treatment with data protection, compute capacity, and ease of use in the center. New developments are further clinical trials, prognostic evaluation, and incorporating advanced health monitoring features to further improve caregiver and patient care.

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