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RESEARCH ARTICLE

Enhancing Chronic Disease Prediction in IoMT-Enabled Healthcare 5.0 Using Deep Machine Learning: Alzheimer's Disease as a Case Study

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ABSTRACT Chronic disease significantly affects health on a global scale. Deep machine learning algorithms have found widespread application in the diagnosis of chronic diseases. Early diagnosis and treatment reduce the chance of a disease getting worse and, as a result, raise related mortality. The main objective of this work is to present a deep machine learning-based approach that provides better results in terms of accuracy. These findings have significance for tailored healthcare 5.0, enabling healthcare professionals to predict chronic disease more efficiently. A comparative examination of the most recent methods has been provided in our work reveals that it might be more advantageous to use the proposed model in which segmentation of the MRI is performed using U-net architecture and then classification is done using transfer learning for chronic disease prediction. Our proposed model provides 96.06% accuracy, it advances our understanding of deep machine learning's potential for chronic disease prediction and emphasizes the need to tailor model selection to specific disease types using data from IoMT enabled devices. In order to make advanced improvement in the field of healthcare 5.0, future studies should focus on refining these models and investigating how well they work with a wider range of datasets.

INDEX TERMS Chronic disease, Alzheimer disease, deep machine learning, IoMT, transfer learning, image segmentation, healthcare 5.0.

I. INTRODUCTION

Chronic diseases are the diseases that endure for a year or longer impede everyday activities. These diseases necessitate continuing medical attention and care. In the US, the most prevalent causes of death and disability are chronic diseases like diabetes, cardiac disease and cancer. These are also leading drivers of the nation's $4.1 trillion in yearly healthcare spending [1] In the US, excessive alcohol consumption is one of the biggest preventable causes of mortality. Figure 1 depicts some most common chronic diseases. Insufficient physical exercise has been linked to heart disease and can increase the incidence of type 2 diabetes in individuals without any other risk factors. Regularly performing physical activities can be helpful to regulate, maintain and control blood pressure, weight, and blood sugar. It can also assist in increasing good cholesterol and decreasing bad cholesterol

The majority of Americans have unhealthy diets, which are high in saturated fat, sugar, and sodium, which increases their risk of acquiring chronic diseases. Nearly every organ in the body gets damaged by cigarette smoking, which also makes people sick and less functional. [3] Chronic Disease Risk Factors involve the following factors depicted in the Figure 2. Chronic diseases are becoming more common worldwide due

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to the demographic shift, particularly in low- and middle-income nations. Management of chronic diseases needs to be ongoing and long-term. They are hard to cure and take a long time to manifest [4]. Multimorbidity, often known as having many chronic conditions, affects at least one in three persons and is linked to worse outcomes and higher healthcare expenses [5]. Four primary non-communicable diseases (NCDs) account for three out of every five fatalities worldwide: diabetes, cancer, chronic lung conditions, and cardiovascular disease [6].

NCDs impact people in all age ranges and in all countries and areas. Although these diseases are frequently linked to older age groups, data indicates that 17 million deaths from NCDs happen before the age of 70. It is estimated that 86% of these premature deaths take place in low- and middle-income nations. All age groups are susceptible to risk factors that lead to non-communicable diseases (NCDs), including poor eating habits, sedentary lifestyles, exposure to tobacco smoke, excessive alcohol consumption, and air pollution [7]

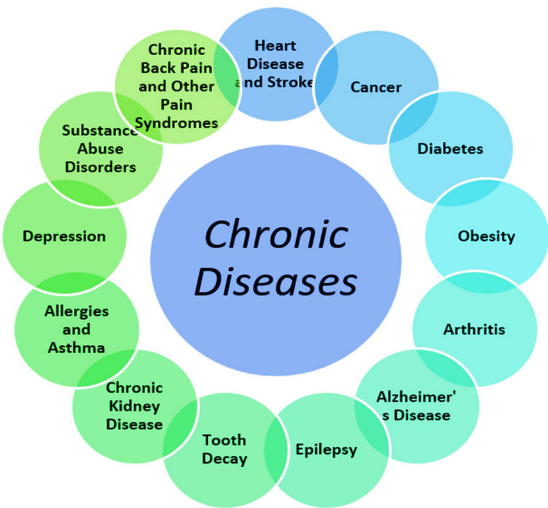

FIGURE 1. Common chronic diseases [1], [2].

FIGURE 2. Chronic disease risk factors [3].

In addition, chronic diseases result in lost productivity at work which costs US$ 138 billion [8]. The direct expenses of chronic diseases to the US health care system come to around US$ 214 billion annually.

The difference between Acute and chronic disease is provided in Figure 3 which shows the complexity of dealing with chronic diseases [9].

In the medical field, detecting chronic diseases is essential since they can have a long latency. Among the most prevalent chronic diseases include hepatitis C, diabetes, stroke, cardiovascular disease, arthritis, and cancer. It has always been advantageous for patients to obtain adequate therapy at an early stage when chronic diseases are diagnosed early. Globally, chronic diseases provide a significant challenge to the healthcare sector. According to the medical statement, the increased death rate among people can be attributed to chronic disorders. The treatments for chronic diseases take up more than 70% of the patient's income. Thus, it is highly important to lower the patient's death risk. The advancement of research in medical sector makes it easier to obtain information on health [10]

Over the past 80 years, a large number of observational studies have investigated the relationship between the risk of mortality and chronic disease and lifestyle risk factors, both separately and, more recently, collectively [11]. The lowest risk of overall mortality and chronic, noncommunicable diseases, especially cardiovascular disease, appears to be associated with being physically active, maintaining a normal weight, abstaining from smoking, and eating. However, there is uncertainty about the relationship between such a healthy lifestyle and life expectancy, especially disease-free life expectancy, a metric that could be more helpful for public comprehension and policy communication than the widely used relative risk estimates [12], [13], [14]. To detect chronic diseases as soon as feasible, numerous investigations have been carried out recently [15], [16]. Based on the physical attributes or lifestyle choices that may eventually lead to a certain chronic disease, several of these studies use computer-aided approaches to detect and forecast chronic diseases. Some aim to investigate possible relationships between two diseases (called complications) to guide for preventing the development of further chronic diseases.

Over the past ten years, several cutting-edge technologies have been developed to quickly gather medical data. These include ultrasonography, MRI (magnetic resonant imaging) readouts, and electronically collected clinical, behavioral, and activity data. These large healthcare data sets may contain more features per observation than total observations due to their high dimensionality. They are cross-sectional, noisy, rare, and lack statistical power. High-dimensional data sets can be used to solve problems using machine learning techniques. [17]. In several fields, machine learning makes a greater contribution. Situated on the cusp of a significant change in healthcare epidemiology, many of the intricate models leverage the greater training data that is currently available [18]. Since the introduction of IT technology, this field has grown exponentially, with countless applications being continuously researched. [19]. Artificial intelligence finds use in various fields, such as disease prediction and cyber security [20]. AI's medical applications are emerging swiftly. More speculation from the global economy was drawn to AI research involving medicine in 2016 than to other projects [21]. Artificial Intelligence (AI) in medicine refers to the use of automated diagnosis procedures and the care of patients in need. Increasing the usage of AI in prescription will enable a significant portion of the work to be automated, freeing up medical professionals' time to handle other, and non-automatable tasks. Consequently, this technology has increasingly substantial applications in the human resources (HR) domain. ML is often classified as either unsupervised (i.e., dealing with grouping disparate groups for a particular purpose) or supervised (i.e., having output variables that are predicted from input variables) By determining sophisticated models and extracting medical knowledge, machine learning (ML) introduces practitioners and specialists to new concepts [22].

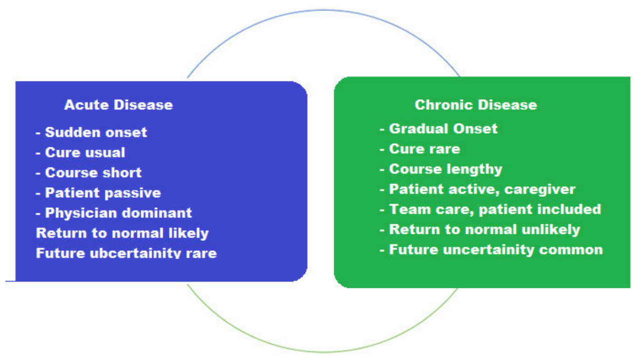

FIGURE 3. Difference between acute and chronic diseases.

Machine learning predictive models can identify improved guidelines for making decisions about the care of specific patients in clinical settings. Under clinical guidelines, these are also capable of diagnosing many disorders on their own [23], [24], [25]. Machine learning is becoming more important in the diagnosis of medical conditions because it makes complex analysis possible. It reduces human error and improves prediction accuracy. These days, it's thought that machine learning algorithms and classifiers are the most trustworthy methods for predicting liver disease, diabetes, heart disease, and cancers [26]. Machine learning can make it easier to analyze patient data, including test results, to identify diseases early on. Through knowledge discovery in the database, low-level data might be transformed into high-level knowledge, enabling early diagnosis by learning about disease patterns [27]. To maximize prediction accuracy and reduce training time, only the critical features required for precise disease prediction should be chosen from the data obtained from the data set after it has been preprocessed, to remove any missing values [28]. For individuals afflicted by chronic disease who require appropriate medical evaluation and treatment information, a disease management system is crucial [29]. Additionally, as self-management is the primary care for people with chronic conditions and is seen as an essential component of treatment, this approach may be helpful to those who require it to improve their health. Mobile applications are a better tool for enabling self-management since they allow patients' health information to be recorded [30]. In order to address a variety of problems in real-time applications, machine learning methods are regarded as classification, clustering, and prediction techniques. They guarantee the performance stability and dependability of the classification and prediction solutions. A few researchers have created effective healthcare systems using machine learning algorithms. Among the various types of algorithms are clustering, SVM, optimization, statistics, and decision trees. Applications for machine learning mostly rely on datasets that are analyzed to find patterns that are then utilized to accomplish particular tasks. The healthcare system possesses the capacity to facilitate the extraction and discovery of hidden patterns within the database in the health sector [31]. In the medical domains, many machine learning techniques employed logistic regression, random forest, and linear regression for the regression purpose and Naïve Bayes, SVM, and decision trees for the classification purpose. By using these algorithms effectively, patients can receive prompt treatment and the death rate can be reduced by early detection Healthcare professionals must use data mining or machine learning approaches to synthesize and analyze these complex facts in order to assist them in making the best decisions possible [10]. In recent years, there has been a noticeable increase in the application of deep machine learning techniques to investigate socioeconomic variables and how they relate to healthcare. This study proposes a transfer learning based strategy for predicting Alzheimer's disease, a chronic neurodegenerative disease, to better grasp the potential of deep machine learning. Intelligent healthcare systems that employ various machine-learning techniques can improve disease prediction to a great extent. While Convolutional Neural Networks (CNN) performs well for image datasets that illustrate human disease, Artificial Neural Networks (ANN) and their related techniques do exceptionally well with numerical datasets. The Internet of Things (IoT), which compiles data from several sensors, makes data collection easier. These are essential for keeping an eye on patients and automated e-healthcare systems. Computers then process the gathered data to make sure the healthcare system runs smoothly. An interconnected network of medical equipment and applications powers the Internet of Medical Things (IoMT), which makes it easier to collect, transfer, and analyze health data. MRI machines and other IoMT-enabled devices first record patient data, making it possible to gather vital data required for the diagnosis of diseases like Alzheimer's. Data is securely transferred to cloud-based platforms for storage and additional analysis after it has been collected. Through the integration of medical devices and digital technology, IoMT plays a critical role in modern healthcare systems, improving patient care, increasing operational efficiency, and facilitating tailored therapy.

Transfer learning enables the use of knowledge gleaned from large-scale datasets, hence enhancing the model's capacity to extract relevant features and patterns from MRI scans and other imaging modalities commonly used in Alzheimer's disease detection. By speeding up model convergence and lowering the need for sizable labeled datasets, transfer learning tackles problems associated with data scarcity in medical imaging studies. Additionally, transfer learning ensures that previously trained models are applicable and efficient by adjusting them to the required characteristics of disease

By employing transfer learning techniques on MRI image data, the proposed study aims to advance early diagnosis and intervention procedures, which will ultimately lead to improved patient outcomes in the management of Alzheimer's disease.

To extract more information from the image and highlight the abnormality, further processing techniques could be applied.

The following are the papers' primary contributions:

- Chronic disease prediction in healthcare 5.0 using deep machine learning is being performed, Alzheimer's is being considered and predicted in four categories, Mild Demented, Moderate Demented, Very Mild Demented, and Non Demented.
- The proposed IoMT-enabled transfer learning model offers a more effective way to accurately predict chronic diseases.
- Image segmentation utilizing U-net, which separates an image's complex visual data into precisely formed segments, enables more advanced image processing.
- The suggested transfer learning approach makes use of ResNet-101's basic architecture to increase its predictive capacity. Particularly tailored Deep Learning Model: ResNet-101, which is intended for MRI-based dementia stage classification, is used for classification, and U-Net was used for segmentation. Through the integration of many prospective parameters, the model considerably enhances the accuracy of Alzheimer's disease prediction.
- Experiments with real data showed the importance of the proposed model and the effectiveness of the algorithm.
- Category-Specific Analysis: To demonstrate how sensitive our model is to the various phases of Alzheimer's disease, we included comprehensive analysis for each category of Alzheimer (mild, moderate, very mild, and non-demented).
- Extensive Statistical Validation: We rigorously validate our results with statistical tests (paired t-tests, ANOVA) and performance measures.

The main objective of our research is to advance medical knowledge by developing a highly advanced deep machine learning-based model that can predict chronic diseases such as Alzheimer's disease. Objective of the proposed study is to employ artificial intelligence and cutting-edge medical imaging technology to transform the early diagnosis and treatment of chronic diseases. With this project, we hope to give medical practitioners a complete solution that combines cutting-edge technology with time-tested medical procedures to deliver quick and extremely accurate diagnostic findings.

The paper is organized as follows: The most recent developments in Alzheimer's disease detection and tracking that have been documented in the literature are highlighted in Section II. Section III covers the study methodologies, dataset election, preprocessing, and proposed TL model; Results and discussion are presented in Section IV, and conclusion and future work are covered in Section V. References are listed at the end of the paper.

II. LITERATURE REVIEW

This section discusses algorithm-related research and presents some algorithms according to their correctness. Machine learning (ML) predictive models can identify better guidelines for choosing particular patient treatment alternatives in clinical practice. These can also diagnose many diseases on their own, according to professional recommendations [32], [33], [34]. The IoT is being swiftly adopted by the healthcare industry to enhance service quality and efficiency through the incorporation of technology into medical devices [35]. It is critical that the healthcare sector incorporates the newest technological advancements in the IoT, AI, and ML domains to reduce human error. The Internet of Things has made it possible to provide high-quality healthcare services that lead to more services being provided and lower prices.

In order to build a prognostic model of the progression of AD dementia, the author in [36], developed a deep learning model Recurrent neural networks (RNNs) are used in this approach to combine MRI data with informative representation and temporal dynamics of individual subjects' longitudinal cognitive assessments. Experiments on a large cohort of MCI patients have demonstrated that the deep learning model can learn useful measures from longitudinal data to characterize the progression of MCI subjects to AD dementia, and that the prognostic model can accurately predict the onset of AD with a high C index 90 scores. In order to forecast metabolic diseases like diabetes and Alzheimer's disease, which are impacting an increasing number of people worldwide, the author used machine learning. A variety of techniques, including Decision Trees, Random Forests, SVM, Gradient Boosting, and Voting Classifiers, have been utilized for predicting Alzheimer's disease. The proposed work shows an 83% accuracy rate on Alzheimer's disease test findings. [37].

A deep neural network intended for binary categorization in medical research is presented in [38]. The network implements three activation functions for hidden layers and does k-folds validation. The model was derived from the ADNI image collection and yielded accuracy scores of 85.19%.

In [39], decision trees and support vector machines have been employed to estimate the probability of Alzheimer's disease based on psychological characteristics such as age, number of visits, and education. In [40], the author proposes an image-based classification method that reduces high dimensionality in brain MRI images of individuals with mild cognitive impairment by utilizing nonlinear manifold learning approaches. This method predicts when moderate cognitive impairment (MCI) will turn into Alzheimer's disease.

This study proposed the use of convolutional neural networks (CNN) and autoencoder MLP to differentiate AD patients from participants with multiple sclerosis (MCI) and hepatic encephalopathy (HC). The method employs scalp EEG recordings, which are simple, noninvasive, and reasonably priced. The study is able to differentiate between people with AD and those with MCI and HC [41].

The Alzheimer's disease Neuroimaging Initiative (ADNI) dataset is used in [42], to classify the various phases of Alzheimer's disease using machine learning and data mining approaches. Even though there isn't a treatment for AD, the test dataset's accuracy is 88.24%

In [43], serum samples from individuals with early Alzheimer's disease (AD) and healthy controls were analyzed using support vector machines (SVMs). The panel of three blood markers identified by the SVM allowed the classification of AD patients from healthy controls. They suggested that blood-based biomarkers could be useful in AD diagnostics, as a screening tool before further classification with CSF biomarkers and imaging.

The author in [44] suggested an automatic speech recognition-based procedure that extracts acoustic and linguistic features from spontaneous speech. Machine learning experiments show that using acoustic features can differentiate between patients and healthy controls, while linguistic features were used to differentiate between Alzheimer's patients and mild cognitive impairment. Combining features can achieve accuracy scores between 80-86%.

In [45], the author presented a classification framework for longitudinal structural magnetic resonance imaging analysis in Alzheimer's disease diagnosis that made use of convolutional and recurrent neural networks. In order to achieve optimal performance, the technique simultaneously learns longitudinal and spatial data as well as the disease classifier. The method demonstrated results for longitudinal MR image analysis, with classification accuracy of 91.33% for AD vs. NC and 71.71% for pMCI vs. sMCI.

In [46] the author suggested to use an MRI image to identify particular aspects of Alzheimer's disease using a Convolutional Neural Network (CNN) framework. The model DEMentia NETwork (DEMNET) provides representations of individual risk, it produces high-resolution maps of disease probability. It provided an accuracy of 84.83 % on ADNI dataset.

In [47], the author presented machine learning methods, on oasis longitudinal dataset for feature extraction and feature selection, followed by classification.

Using brain MRI data, the author in [48] proposed a unique deep learning model for multi-class Alzheimer's disease detection and classification. With an accuracy of 73.75% on the Open Access Series of Imaging Studies database, the model, which utilized deep convolutional network, demonstrated how machine learning techniques might be applied to early diagnosis. The algorithm presented by the author in [49], selected specific image blocks and calculates textures for each block. To find pertinent features, a feature selection method with bootstrapping is applied to the resulting textures. The ADNI database's baseline MR scans of 812 participants are used to validate the approach, which yields a sensitivity 89.58 and specificity of 85.82% for AD/NC categorization.

The author proposed a novel classifier in [50], for brain magnetic resonance images (MRI) using downsized kernel principal component analysis (DKPCA) and multiclass support vector machine (SVM). The method uses multiobjective optimization to minimize retained principal components and ensures accurate classification. The DKPCA-based technique was tested on synthetic data and the OASIS MRI database.

Using an adaptive neuro fuzzy inference-based classifier, the author identified Alzheimer's disease using MRI brain pictures into three categories: moderate, normal, and AD in [51]. Following segmentation, four features are extracted, and the classifier is trained using these features. In terms of classification accuracy, the ANFIS classifier performed better than the SVM classifier. In order to increase classification accuracy, image processing methods including segmentation and feature extraction were used with MRI data from the ADNI dataset, which included 150 individuals.

The author in [52], presented two deep learning models for classification of Alzheimer's disease. Making use of texture and other features from structural MRI. Both models made use of stacked auto-encoder deep neural networks (DNNs), feature selection, and subcortical area-specific feature extraction. In dementia patients, the models distinguished AD from mild cognitive impairment and cognitive normalcy. The models achieved tenfold cross-validation accuracy of 56.6% and 58.0%, as well as competitive classification accuracy of 51.4% and 56.8% in the evaluation of public domain data.

The author introduced AD Pattern Similarity (AD-PS) scores in [53], a tool for assessing Alzheimer's disease risk. The Alzheimer's disease Neuroimaging Initiative study's structural MRI and cognitive test data were used to model conditional probabilities, which were then transformed into scores using logistic regression. The study analyzed how well they performed in various scenarios and examined correlations between conversion durations from moderate cognitive impairment to AD using Cox proportional hazards regression.

The author applied a hippocampus texture-based classification technique for Alzheimer's disease (AD) using MRI images from the ADNI dataset. The procedure makes use of

TABLE 1. Comparison of accuracy and limitations of different deep machine learning methods.

Ref	Method	Disease	Accuracy	
[36]	Deep RNN	Alzheimer's disease	C index 90%	The study does not explicitly outline a segmentation process in its methodology and dataset is limited.
[37]	Decision Tree, Random Forest, Support Vector Machine, Gradient Boosting, and Voting classifiers	Alzheimer's disease	83%	The study does not explicitly outline a segmentation process in its methodology.
[38]	DNN	Alzheimer's disease	85.19%	The classification is performed only on 20% of the data
[39]	Decision Tree, Support Vector Machine,	Alzheimer's disease	85%, 83%	The study does not explicitly outline a segmentation process in its methodology.
[40]	Support Vector Machine	Alzheimer's disease	56.1%	The dataset is limited in size.
[41]	CNN	Alzheimer's disease	80%	The dataset is limited in size.
[42]	Generalized Linear Model	Alzheimer's disease	88%	The dataset is not balanced and segmentation is not performed.
[43]	Support Vector Machine	Alzheimer's disease	81.7%	Segmentation is not performed and the limited size of the Dataset and Alzheimer is not classified into subclasses
[44]	Support Vector Machine	Alzheimer's disease and MCI	80-86%	The dataset is small just 75 samples, AD is not further classified
[45]	CNN and RNN	Alzheimer's disease and MCI	91.33%	The study does not explicitly outline a segmentation process in its methodology
[46]	CNN	Alzheimer's Disease	84.83 %	Segmentation is not performed
[47]	Gaussian process algorithm	Alzheimer's disease	-	Handcrafted features and segmentation is not outlined in the methodology
[48]	DCNN	Alzheimer's disease	73.75%	The study does not explicitly outline a segmentation process in its methodology and size of Dataset is limited.
[49]	KNN , Random Forsest,SVM	Alzheimer's disease	87.39%	Hnad crafted feature extraction and many features are excluded from the study
[50]	DKPCA + MKSVM	Alzheimer's disease	92.5%	The study does not explicitly outline a segmentation process in its methodology
[51]	ANFIS Classifier and SVM	Alzheimer's disease	81.22%	The dataset is limited in size.
[52]	DNN	Alzheimer's disease	58%	Higher rate of misclassification of patients as AD
[53]	Logistic Regression	Cognitive Normal N and Alzheimer's Disease	87.1%	Potential confounding factors due to the quality of brain tissue segmentation, which may result in overlap among areas.
[54]	SVM and KNN	Alzheimer's disease	85%	Alzheimer's is not classified in its types
[55]	CNN	Alzheimer's Disease	86.60%	Small number of subjects used in training and testing phases.

deep learning, texture analysis, and image processing. In the AD-MCI, AD-NC, and MCI-NC categories, the approach yielded 72.5%, 85%, and 75% accuracy, with AD-NC achieving the greatest accuracy of 85% [54].

An end-to-end learning strategy for four binary classification tasks pertaining to Alzheimer's disease (AD) using a volumetric convolutional neural network (CNN) model has been presented in [55]. For pMCI vs. sMCI, the approach used supervised transfer learning; for AD vs. NC, it used convolutional autoencoder (CAE)-based method. Gradient-based visualization was used to identify biomarkers linked to AD and pMCI. Experiments using the ADNI database showed accuracies of 86.60% and 73.95% for the pMCI and AD classification tasks, respectively.

Table 1, presents a brief comparison of different methods in terms of accuracy and the limitations of the existing studies.

III. METHODOLOGY

To fill in the gaps in medical image processing and related fields, machine learning techniques are essential for evaluating and predicting the characteristics of medical images. In particular, deep learning is essential for the early identification of medical disorders in images. Deep machine learning has enormous potential for treating chronic diseases, benefiting patients as well as healthcare professionals. Image segmentation splits a digital image into discrete groups of pixels, or image segments, to help with object detection and related tasks. For this purpose, the U-net model has been put into practice. For chronic disease prediction, an IoMT enabled Transfer Learning model leveraging the ResNet 101 architecture is presented, which recognizes the effectiveness of deep machine learning in chronic disease diagnosis. By reusing pre-trained models and representations, transfer learning transforms model building and is especially helpful in difficult areas such as medical imaging. Our model excels in chronic disease prediction by using features extracted from large datasets in its first levels and optimizing the succeeding layers for the target objective. Precise prediction of chronic diseases enables medical practitioners to start early interventions and individualized care, improving patient outcomes and encouraging proactive disease management to reduce the risk of complications.

A. DATASET

Alzheimer MRI dataset [56] from Kaggle, is used in this study. These are MRI images of size 128 × 128. There are 6400 MRIs in the dataset that are further classified into four subclasses; mild demented, moderate demented, non-demented, and very mild demented. 896 MRIs are of mild demented, 64 moderate demented, 3200 images are non-demented and 2240 are very mild demented. Overall there are 6400 MRIs of which, 3200 are normal and 3200 are abnormal. Figure 4 presents the classes of the Alzheimer disease dataset.

Those who fell into the group of ''very mild demented'' were those who had early indications of cognitive decline and frequently showed mild cognitive impairments that might not have a major influence on day-to-day functioning. The term ''mild demented'' referred to people who had mild cognitive impairment, which was defined as perceptible cognitive impairments that would interfere with day-to-day functioning but did not yet match the diagnostic criteria for dementia. Those who fell into the category of ''moderate demented'' had moderate to severe cognitive impairment, causing notable impairments to memory, cognition, and day-to-day functioning. Finally, MRIs of people who were not demented were included in the ''non-demented'' category.

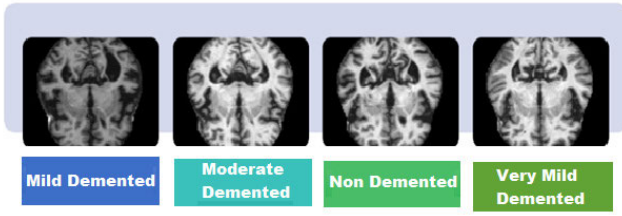

FIGURE 4. Classes of Alzheimer's disease Dataset.

The most effective method for predicting chronic diseases is to use a deep machine learning framework with a large dataset that consists of images. A deep machine learning method, transfer learning is used to identify complex patterns in data related to Alzheimer's disease. It improves previously trained models by enabling them to include characteristics from several modalities. This technique captures complex patterns across heterogeneous data sources, improving the forecast accuracy and reliability of chronic disease.

B. IMAGE SEGMENTATION USING U-NET

Segmentation is a fundamental concept in image processing that has many benefits, particularly for medical imaging tasks like Alzheimer's disease diagnosis. Segmentation makes it possible to do focused analysis and interpretation by accurately identifying relevant areas of brain abnormalities or structures from MRI images in Alzheimer's disease.

Segmentation is used to precisely isolate specific anatomical structures and regions of interest within the brain, serving as a crucial feature of MRI image processing, particularly for the detection of Alzheimer's disease. Important regions, such as the hippocampus, which is also known to exhibit neurodegenerative alterations associated with Alzheimer's disease, are identified through segmentation techniques. By eliminating noise and extraneous information, this approach enhances the overall quality of data analysis, allowing deep learning models to focus on the most relevant features present in the MRI images. Additionally, the dimensionality of the input data is reduced by segmentation, which increases the computational efficiency of the model and leads to improved training and classification accuracy. Consequently, more accurate predictions regarding the different phases of Alzheimer's are enabled by providing the model with well-defined regions of interest

The U-Net architecture allowed for the accurate segmentation of brain images, which was a crucial step in our study of Alzheimer's disease. The U-Net model, which is well-known for its effectiveness in semantic segmentation tasks, proved

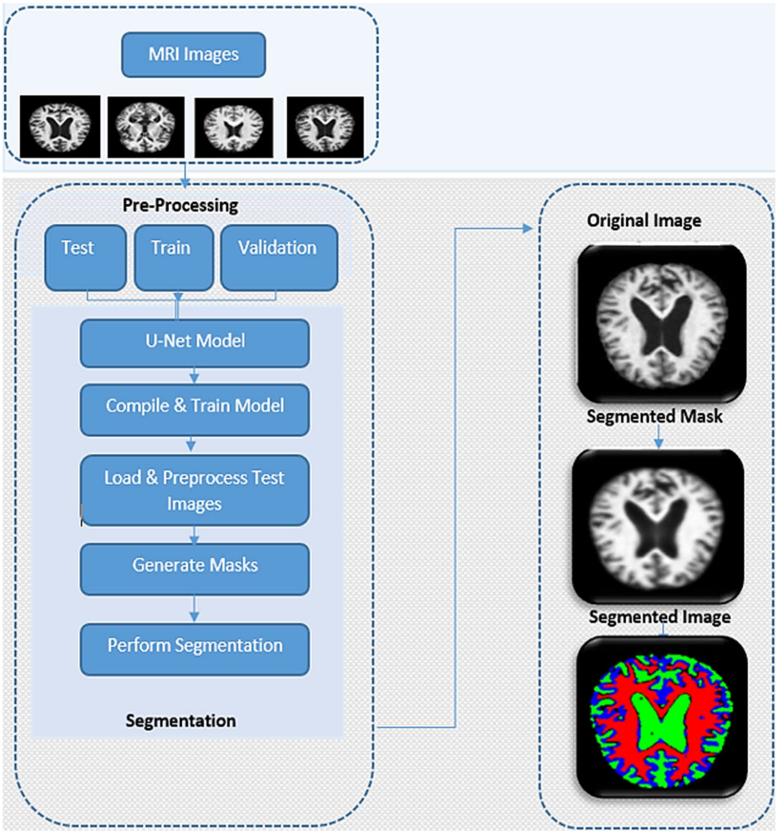

FIGURE 5. Segmentation of MRI Using U-net Architecture.

to be adept at recognizing intricate spatial relationships in the images, which was necessary for differentiating the regions of interest, affected by Alzheimer's disease. Using an encoder-decoder structure with skip connections, the U-Net architecture was able to extract high-level features required for segmentation while maintaining fine-grained information.

The study trained and evaluated a U-Net model using MRI images of Alzheimer's disease. 10 iterative epochs, or complete runs of the training dataset, were used to train the model. The algorithm was trained to precisely identify abnormalities associated with disease and segment brain areas. Through iterative parameter optimization, the model was able to improve its segmentation performance

In addition, employing strategies like data augmentation, regularization, and early halting assisted in preventing overfitting and improving the model's capacity for generalization.

Additionally, segmented images offered academics and medical professionals clear visual representations that help in improved diagnosis and aided in the understanding of complex imaging data. Furthermore, segmentation acted as a prelude to later machine learning algorithms, facilitating the creation of decision support systems and prediction models for early disease identification and customized treatment strategies. In general, the use of the U-Net architecture for segmentation and the ensuing examination of segmented images produced priceless revelations into the pathology of Alzheimer's disease, opening the door to more accurate diagnosis, prognosis, and treatment approaches.

Figure 5 represents the process of segmentation of MRI images using U-net, Table 2 provides a description of symbols of the U-net algorithm and Table 3 presents the segmentation algorithm of the U-Net model Figure 6 represents the original MRI conversion into masks and ultimately into Segmented Images.

TABLE 2. Variables and symbols utilized in the U-NET algorithm.

Symbol	Description
T	MRI image dataset (images)
C	Representing the set of configuration options for the segmentation process.
M	Segmented masks for each image

C. TRANSFER LEARNING AND CONVOLUTIONAL NEURAL NETWORK (CNN)

ConvNet, often known as CNN, is a deep learning algorithm that, retrieves the input, applies weights and biases to its many properties, and then separates one from the other [57]. The main benefit of utilizing CNN is that, in comparison to other algorithms, it requires less work to preprocess the data

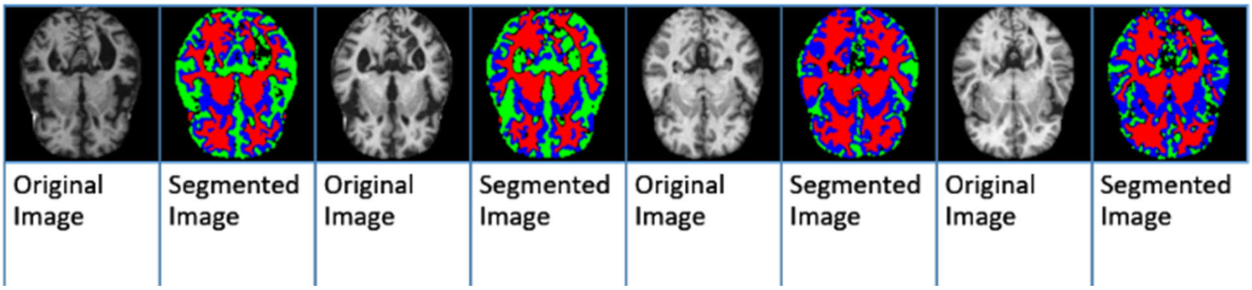

FIGURE 6. Segmented images.

TABLE 3. Algorithm of U-net.

```
Algorithm: Segmentation of MRI Images
BEGIN
  M ← Empty set
  Preprocessing_completed ← False
  Segmentation_completed ← False

  if C includes preprocessing then
    Apply preprocessing steps (e.g., resizing, normalization) to the MRI
images.
    Set Preprocessing_completed to True
  end if

  if C includes segmentation then
    Load a pre-trained segmentation model (e.g., U-Net) for MRI image
segmentation.
    Train the model on the preprocessed MRI dataset.
    Set Segmentation_completed to True
  end if

  foreach image m in T do
    Perform segmentation using the trained model:
    Generate segmented mask for image m using the segmentation model.
    Add segmented mask to M.
  end foreach

  return M (Segmented masks for each image)
END
```

because it can automatically learn to optimize its filters [58]. A DNN structure that incorporates convolutional processing, CNN [59] may translate-invariantly classify input data based on hierarchical structure and is capable of representation learning. Convolutional, batch-normalization, pooling, fully linked, and other layers are typically seen in CNNs.

The convolutional layer is its central component. The task of extracting features from the input image is performed by the convolution layer.

The convolution layer has many convolution kernels. As with feed-forward neural networks, each component that forms the convolution kernel has a corresponding weight coefficient and bias value. Reducing parameters and extracting local features are possible outcomes of this technique. With its ability to extract local features and minimize parameters (via weight sharing), CNN is especially well-suited for the image processing industry. The application range of CNN in the medical area is greater than other models because of the abundance of picture data in the field. CNN can handle spatial dimension problems, however, it is unable to analyze time-dimension data. Layers that use convolution to extract local information (such edges) from an input image are the basis of convolutional neural networks, or CNNs. Within a convolutional layer, every node is coupled to a small fraction of spatially related neurons. To find the same local feature throughout the input image, the nodes of the convolutional layers exchange connection weights, forming convolutional kernel. In order to reduce computational complexity, a pooling layer follows each sequence of convolution layers.

Transfer learning, also known as fine-tuning, is a substitute for randomized weight initialization in which the CNN's weights are taken from a network that has previously been trained on a bigger dataset. In medical imaging, transfer learning or fine-tuning has also been investigated. In-depth analysis and comparison findings between training from scratch and fine-tuning on a few medical applications are presented in [60]. Research demonstrates that fine-tuning typically works better than starting from scratch. CNNs that have been fine-tuned have been applied to cardiac imaging [61], interstitial lung disease classification [62], and ultrasound image localization [63]. So Transfer learning enhances patient care by instructing generalist physicians on the front lines of healthcare [64]. Accurate disease prediction is essential for human health in the smart healthcare industry 5.0. The field of the Internet of Medical Things has expanded rapidly in the past few years, going from tiny wristwatches to massive aircraft [65]. However achieving a balance between accuracy and interpretability in predictions is crucial in a medical setting [66]. The proposed method addresses issues related to data scarcity in medical imaging by improving prediction performance while lowering training time and data needs. Moreover, transfer learning makes domain adaptation easier, allowing models to adjust to differences in imaging procedures and disease presentations in various healthcare

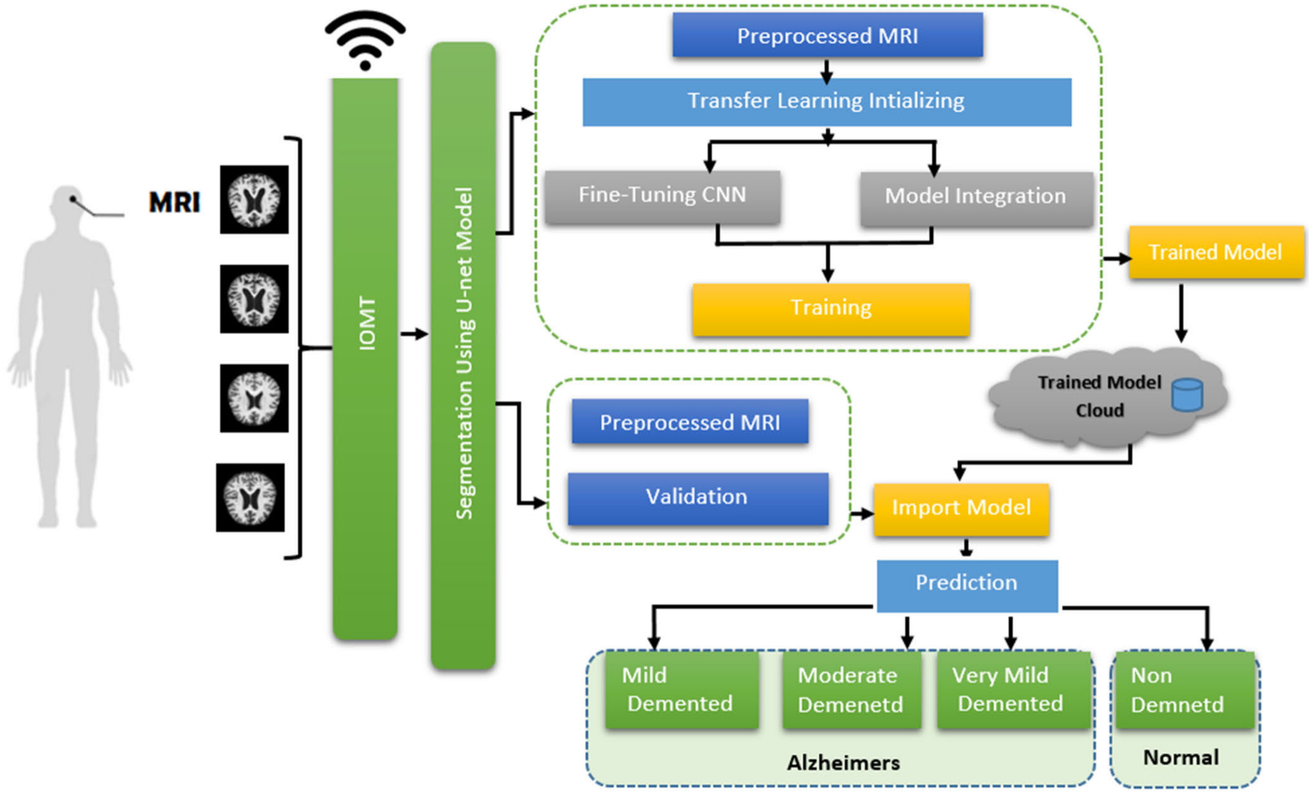

FIGURE 7. IoMT enabled transfer learning model for Alzheimer's (chronic disease) prediction.

environments. Medical professionals are assisted in making decisions and planning treatments by their capacity to transfer knowledge from related areas, which improves interpretability and model transparency. In general, transfer learning is a useful technique for enhancing model resilience, interpretability, and generalization for predicting chronic diseases from medical imaging datasets.

The proposed model for predicting Alzheimer's disease, a chronic disease, utilizes a transfer learning approach as shown in Figure 7. The MRI dataset is first acquired and preprocessed, which includes normalization, and standardization. Segmentation is performed using U-Net which allows for the isolation of only necessary areas, allowing for a more accurate study of anatomical data. It starts with the division of MRI into training, validation, and testing sets.

The proposed comprehensive method that uses transfer learning, and ResNet 101 which is type of convolutional neural networks (CNNs) on MRI data to predict Alzheimer's disease begins with data acquisition from the sensory layer. The sensory layer consists of IoMT devices and sensors. This process involves obtaining MRI datasets that include brain images from individuals with Alzheimer's disease as well as healthy patients. The collected data is then carefully preprocessed, including Segmentation, for which U-Net is model is trained, and after masking it performs segmentation. The segmented MRIs are used after normalization and standardization, to guarantee consistency and get it ready for the next round of model training. Then, using insights from large datasets, transfer learning is used to initialize pre-trained CNN models. Figure 8 represents the transfer learning Model which takes segmented MRI.

The MRI data is used to fine-tune these models to capture spatial elements relevant to the pathogenesis of Alzheimer's disease. Once the CNN models have been adjusted, they are combined to create a single architecture that is focused on disease prediction. After integration, the model is trained on a certain training set and sent to the cloud. Validation is performed and the model is imported from the cloud and its predictive performance is tested. Predictions are made using the trained model following testing.

The model's performance is then carefully assessed using measures like accuracy to see how well it predicts Alzheimer's disease. The process ends after the performance review is finished, denoting the end of the workflow. This sophisticated method highlights the skillful application of transfer learning to increase the precision and dependability of Alzheimer's disease prediction, outlining a methodical and expert framework for utilizing deep machine learning in medical image analysis

The ResNet-101 architecture employs convolutional and max-pooling layers to extract spatial information. In the fusion layer, spatial and temporal elements are combined to

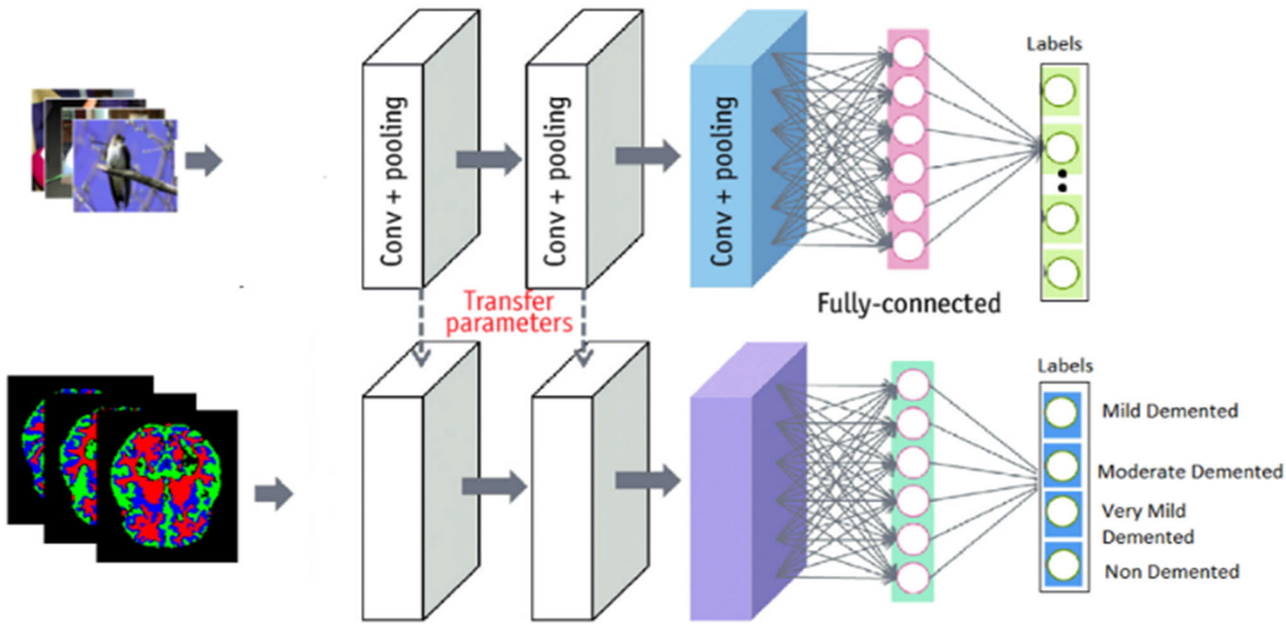

FIGURE 8. Transfer learning for Alzheimer's disease prediction.

create a comprehensive representation. The model is trained using fully connected layers with dropout to prevent overfitting. The testing set's accuracy, precision, recall, and F1-score are among the evaluation metrics, and hyperparameter tuning is done iteratively. Table 4 describes symbols of the Transfer learning algorithm and Table 5 presents the Transfer Learning algorithm of the model In addition to providing a thorough understanding of the patient's health profile, this approach increases prediction accuracy and makes more tailored and effective healthcare treatments possible for the management and prevention of chronic diseases.

Comprehending the larger environment in which IoMT functions is crucial. The MRI scans are sourced from a healthcare data repository; nevertheless, the IoMT framework is necessary for the possible use of this data in actual clinical situations. IoMT specifically refers to the networked ecosystem of health apps and medical equipment that makes real-time data collection, transfer, and analysis possible. In a real-world setting, IoMT would make it easier to obtain MRI images straight from imaging equipment, enabling ongoing patient monitoring and prompt actions. Furthermore, the idea of IoMT includes the infrastructure needed to send these images securely to cloud-based platforms for processing, giving medical practitioners quick access to critical data. This connectedness facilitates workflows that are more effective and improves decision-making when it comes to managing chronic diseases like Alzheimer's. Therefore, even though the images used in this study were obtained from healthcare repository, the IoMT framework shows how this kind of data could be used in a coordinated healthcare setting to enhance patient outcomes by employing proactive monitoring and treatment approaches.

The study's shortcomings include questions regarding the predictive models' generalizability and the need for additional research, as well as the lack of diverse, high-quality datasets for training and validation and a lack of clarity regarding the logic underlying machine learning algorithms' predictions.

TABLE 4. Variables and symbols utilized in the algorithm.

Symbol	Description
T	Represents the input dataset of MRI images, where each image is segmented
C	Configuration options that determine the preprocessing and transfer learning steps
R	Represents the output, which is a set of predicted labels for each image in the dataset"
m	Represents each segmented MRI image in the dataset T

The Internet of Medical Things (IoMT) plays a critical role in enabling efficient, scalable, and remote healthcare delivery, which is central to the design and intended application of our Alzheimer's disease prediction.

Despite the fact that our study made use of an existing Kaggle dataset, this decision offered a controlled setting for the development and validation of our model, guaranteeing its resilience prior to practical use. The real-time collection and secure transfer of MRI images from linked imaging devices to our predictive model which might be implemented on edge and cloud platforms for smooth processing would be made possible in real-world healthcare settings by an IoMT-enabled framework. In order to facilitate frequent assessments and

TABLE 5. Algorithm of proposed model.

Algorithm: Chronic Disease Prediction using Transfer Learning

Input: Segmented MRI image dataset (images) represented T
Output: Predicted labels for each image, represented as *R*
BEGIN
R ← Empty set
Preprocessing_completed ← False
Transfer_learning_completed ← False
 	
if C includes preprocessing then
Apply preprocessing steps (e.g., resizing, normalization) to the segmented MRI images.
Set Preprocessing_completed to True
end if
 	
if C includes transfer_learning then
Load a pre-trained model (e.g., ResNet101) for image classification.
Fine-tune the model on the preprocessed segmented MRI dataset.
Set Transfer_learning_completed to True
end if
 	
foreach segmented image m in T do
Make a prediction using the trained model:
if the model predicts "Mild Demented" then
Add "Mild Demented" to R
else if the model predicts "Moderate Demented" then
Add "Moderate Demented" to *R*
else if the model predicts "Non Demented" then
Add "Non Demented" to *R*
else if the model predicts "Very Mild Demented" then
Add "Very Mild Demented" to *R*
 	
end if
end foreach
 	
return R (Predicted labels for each image)
END

maybe act sooner in the course of the disease, this framework envisions a seamless data flow from IoMT devices at the point of care to centralized or distributed processing units. IoMT is therefore still a key element of the suggested system, supporting both the model's architecture and its capacity to provide scalable, real-time predictive insights in healthcare contexts supported by IoMT, even though the current data source is static.

IV. EXPERIMENTAL FINDINGS AND RESULTS

Transfer Learning (TL) is a method in deep machine learning (DML) used to repurpose a model developed for one task to be applied to another related task. By utilizing an already-existing network architecture that has undergone extensive training on a substantial dataset, this method considerably minimizes the duration and resources required for the training of deep Convolutional Neural Networks (CNNs). Compared to building a network from scratch, TL is generally faster and less resource-intensive.

TL is frequently used with DML models that have been developed for large-scale image classification projects. The use of ResNet-101 for disease prediction offers significant advantages, making it a highly effective tool for medical image analysis. With its deep architecture comprising 101 layers, intricate patterns and features can be captured, enhancing the precision of disease prediction. The incorporation of residual learning mitigates the vanishing gradient problem, allowing efficient training even with a large number of layers. Additionally, ResNet-101 benefits from transfer learning, as it can be fine-tuned on specific medical datasets after being pre-trained on extensive general datasets, reducing the need for large labeled medical datasets and accelerating the training process.

Deep learning applications often employ TL because it allows a pre-trained network to be adapted for a new task. Fine-tuning a pre-trained network is significantly faster and easier than training a network from scratch with randomly initialized weights. This process enables the quick transfer of learned features to a new task, often with fewer training images required.

The incorporation of IoMT principles is nevertheless essential to the larger context of our research, even if the dataset used in this study came from Kaggle and did not entail real-time data collection through IoMT devices. Future healthcare systems are expected to be greatly aided by the Internet of Medical Things (IoMT), as linked medical equipment will make it easier to collect real-time health data, monitor patients continuously, and intervene promptly.

In our research, we adapted the TL model for classifying Alzheimer's disease using MRI images. For this experiment, the MATLAB 2020a tool was used to customize the pre-trained model according to the specific requirements of the study. ResNet 101 robust architecture and ability to leverage prior knowledge improve the model's generalization to new, unseen medical data, and ensuring reliable and consistent performance. Modifications were made to the first layer and the last layers of the model. The Alzheimer's MRI image dataset was divided into training (80% of the images) and validation (20% of the images) sets. We used an 80/20 split for training and validation, ensured that 20% of the data was put aside for model validation, to help alleviate some of the problems caused by the scale of the dataset. An initial evaluation of the model's performance is given via this internal validation.

During different phases of our technique, we employed a combination of cloud-based platforms and local computer resources in our study. In particular, segmentation with the U-Net model was carried out on Google Colab, which offered GPU acceleration, enabling processing at a speed faster than with a CPU-only configuration. The segmentation time was greatly shortened as a result, increasing its viability for clinical applications.

TABLE 6. System setup and configuration.

Tool or device	Description
Desktop System	Windows 10 Pro N (Version 21 H1)
Processor Speed	Intel ® Core ™ i7-4770 CPU @ 3.40GHz
RAM	18.0 GB
MATLAB version	2020a

TABLE 7. Training settings and hyper parameters.

Training Preferences	Considerations
Number of epochs	10
Iteration per epoch	331
Total Iterations	3310
Initial Learning rate	0.001

A desktop computer running Windows 10 Pro N (Version 21 H1), MATLAB 2020a, with an Intel ® Core TM i7-4770 CPU running at 3.40GHz with 18 GB of RAM was used for the training and validation operations in our study. The training was done with a single CPU without the acceleration advantages of GPU processing due to hardware constraints.

Our model underwent 3,310 iterations in total throughout its training, which was divided into 10 epochs of 331 iterations each. Throughout the training procedure, a consistent learning rate schedule was maintained with an initial learning rate of 0.001. With 50 iterations for validation, the training took about 1125 minutes (18 hours and 45 minutes) to finish.

Given the single-CPU setup, the training time was considerable; however, when the model is deployed in a more optimized hardware environment, such as a system with GPU acceleration or cloud-based infrastructure the inference time per image is anticipated to be much faster, making the model viable for clinical use. Our training took about 1,125 minutes (18 hours and 45 minutes) across 10 epochs on a single-CPU machine with an Intel® Core™ i7-4770 CPU and 18 GB of RAM. We recognize that faster inference is necessary for real-time clinical application, even if our arrangement produced a high accuracy rate of 98.19% on the MRI dataset. Inference durations per image might be drastically lowered to a few seconds with the use of a GPU or cloud-based computing, which would enable the model to be used for real-time diagnosis. Furthermore, our method is made to scale across a range of hardware configurations that are frequently found in clinical settings, including cloud resources and high-performance local workstations. Because of its flexibility, our model can accommodate the various computational capacities and real-time requirements of healthcare facilities.

IoMT can be extremely helpful in predicting Alzheimer's disease by facilitating remote patient monitoring, gathering long-term health data, and combining many data streams from imaging and wearable technology. The model's accuracy and suitability for use in clinical settings may be further improved by the insights derived from such data. Although the primary focus of our current study was an analysis of pre-existing MRI datasets, the techniques created can be modified and applied in IoMT frameworks, which can help progress predictive healthcare models.

During the preprocessing, segmentation, and model training stages, a thorough approach using a variety of methodologies was used to handle any possible overfitting. To guarantee constant image quality and reduce artifacts, preprocessing techniques including normalization and standardization were applied. Furthermore, U-Net segmentation was used to segregate important brain regions, which helped the model concentrate on pertinent variables and cut down on noise. Regularization strategies, were used during ResNet-101 model training, To find the ideal balance between model complexity and generalization ability, hyperparameter adjustment was done iteratively. The model's generalizability and robustness for predicting Alzheimer's disease were enhanced by these combined techniques.

Table 6 and Table 7 in the study detail the implementation environment or System Setup and Configuration and Training Settings and Hyperparameters, respectively, which were optimized for the best performance. The TL algorithm was applied to a dataset of 6400 MRI images of Alzheimer's disease, which was split into 5120 images for training and 1280 images for validation. The equations in [65] Eq. (1) through Eq. (6) have been employed for the computation of the parameters, as illustrated below.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Specificity = \frac{TN}{TN + FP} \tag{3}$$

$$Senstivity\,(Recall) = \frac{TP}{TP + FN} \tag{4}$$

$$Misclassification\ Rate = \frac{FP + FN}{TP + TN + FP + FN} \tag{5}$$

$$F1Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{6}$$

These metrics were computed to evaluate the effectiveness of the proposed TL model in classifying Alzheimer's disease MRI images. The detailed analysis and validation confirmed the model's robustness and suitability for this specific medical imaging task. The confusion matrix depicting the performance of the proposed IoMT-enabled TL model during training is presented in Figure 9, while its validation performance is illustrated in Figure10. The accuracy along with results and iteration details of proposed model is presented in Figure 11.

Figure 9 illustrates the suggested IoMT enabled Intelligent TL model prediction for the categories of Alzheimer's disease during the training phase, 5120 MRI segmented images are being sued for the training phase. It matrix shows how well the model performed in categorizing four groups: Very Mild Demented, Moderately Demented, Non Demented, and Mildly Demented. The model accurately detected 5048 cases of mild dementia, but incorrectly classified 72 cases into other categories: 25 were labeled as moderately demented, 20 as non-demented, and 27 as very mildly demented. 5004 cases in the Moderate Demented category were properly predicted by the model, however 116 cases were misclassified (90 as Mild Demented and 26 as Non Demented). The model correctly predicted 4941 cases for non-demented individuals, but misclassified 179 cases (of which 95 were classified as moderately demented and 84 as very mildly demented). Finally, the model performed best in the Very Mild Demented category, with 5118 accurate predictions and only 2 misclassified cases (one as Non Demented and one as Mild Demented). Out of 20480 cases, 20111 predictions were accurate overall, yielding an accuracy rate of 98.19%. This high accuracy shows that most cases across all categories are accurately classified by the model.

The hardware and computational expenses of implementing the suggested transfer learning (TL) paradigm must be taken into account when incorporating it into current clinical procedures. An Intel® Core™ i7-4770 CPU running at 3.40GHz with 18 GB of RAM was required for the model's training phase, which took about 1125 minutes (18 hours and 45 minutes). For real-time applications in a clinical situation, this configuration might not be adequate. It is advised to use cloud-based infrastructure or systems with GPU acceleration to attain the best possible performance and efficiency.

It is anticipated that these improvements will drastically cut down on inference times per image, giving clinicians' prompt diagnostic assistance.

To ensure effective operation, certain hardware and computational criteria must be met when integrating the suggested transfer learning model for Alzheimer's disease categorization into current clinical processes. It took over 1125 minutes (18 hours and 45 minutes) to train the model on an Intel® Core™ i7-4770 CPU with 18 GB of RAM over 10 epochs, underscoring the need for more reliable systems in clinical settings. It is advised that healthcare facilities use GPU acceleration, such as the NVIDIA GeForce RTX 3060 or Tesla V100, to maximize performance. This might cut training time by up to 80%, to about three to four hours. With enhanced hardware, the inference time per MRI image should drop to a few seconds, allowing the model to be used in real-time. Larger datasets should be handled with at least 16–32 GB of RAM for optimal performance, and cloud-based infrastructure like AWS or Google Cloud can help with scalability and remote accessibility, improving the model's incorporation into clinical practice.

In order to facilitate a smooth integration into healthcare practices, the integration process must also take into consideration the computational resources required to ensure consistent performance and dependability across different clinical situations.

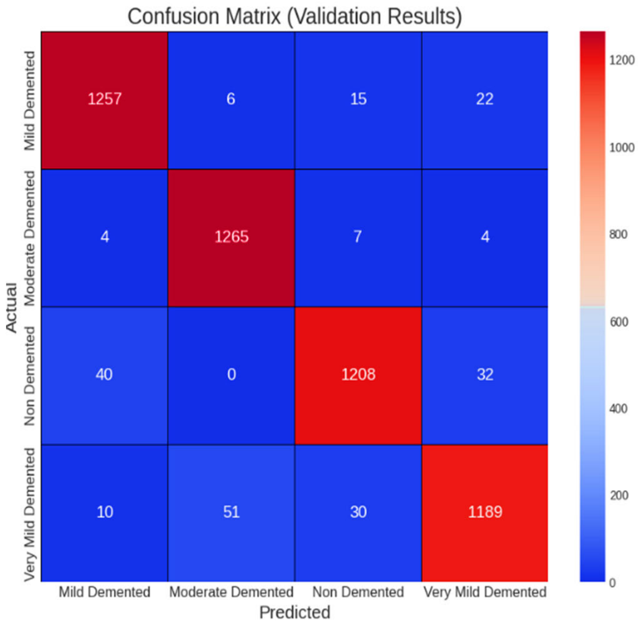

FIGURE 9. **Training of the proposed IoMT-Enabled intelligent system for alzheimer's disease prediction.**

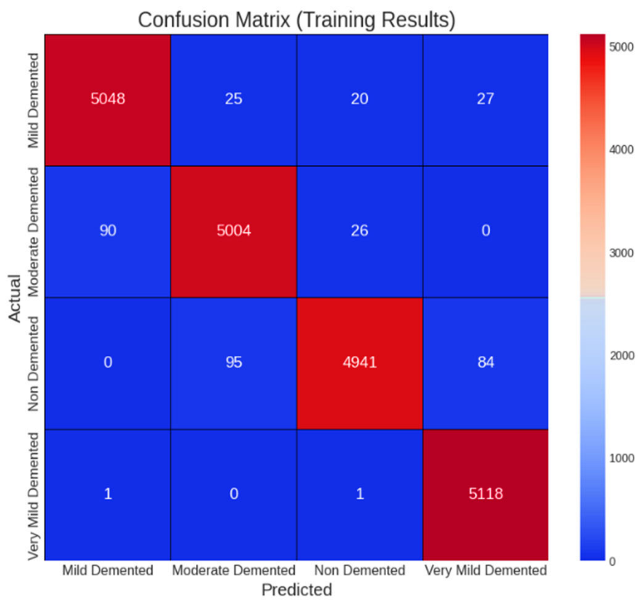

FIGURE 10. **Validation of the proposed IoMT-Enabled intelligent system for alzheimer's disease prediction.**

The proposed model's validation performance across four diagnostic categories, Mildly Demented, Moderately Demented, Non Demented, and Very Mildly Demented—is illustrated by the Figure 10 of confusion matrix of validation. The model correctly classified 1257 cases in the Mild Demented class; 43 cases were misclassified, with 6 being

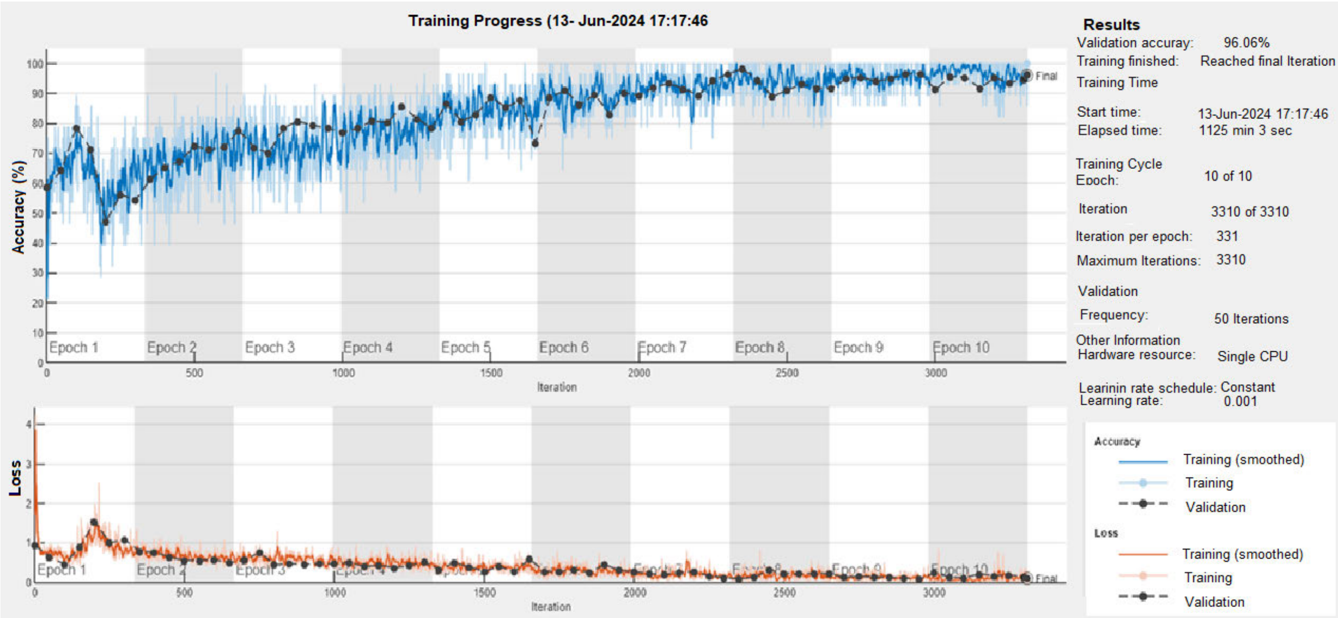

FIGURE 11. Training of the proposed IoMT-Enabled intelligent system for Alzheimer's disease prediction.

classified as Moderately Demented, 15 as Non Demented, and 22 as Very Mild Demented. 1265 instances in the Moderate Demented category were properly predicted, however four were mislabeled as Very Mild Demented, seven as Non Demented, and fifteen as Mild Demented. Twelve thousand correctly predicted cases that were not demented, but seventy-two cases were misclassified, forty of them as Very Mild Demented and forty as Mild Demented. In summary, 1189 cases in the Very Mild Demented group were correctly categorized, but 91 cases were incorrectly classified as 10 cases of mild dementia, 51 cases of moderate dementia, and 30 cases of non-dementia. Out of 5120 occurrences, 4919 correct predictions were made, yielding a validation accuracy of 96.06%. This high classification accuracy demonstrates how well the model works to categorize most cases in all diagnostic categories. Performance evaluation of the proposed IoMT-enabled intelligent system has been presented in Table 8 and Figure 12 illustrates a comparison of validation and training metrics.

A trained model was used to assess the performance of the suggested IoMT-enabled intelligent system, and the results were shown for both the training and validation datasets.

High accuracy was attained in all categories during the training phase: 99.14% for Mildly Demented, 97.92% for Moderately Demented, 97.23% for Non-Demented, and 98.42% for Very Mildly Demented. Strong sensitivity values of 98.46%, 96.89%, 98.28%, and 98.27%, respectively, were also noted. The range of the constant high specificity scores was 99.39% to 99.67%. All categories had exceptionally low misclassification rates: 0.86% for mildly demented, 2.08% for moderately demented, 2.77% for non-demented, and 1.58% for very mildly demented. F1 scores, which include recall and precision, again showed high values, with 98.80%, 97.39%, 97.75%, and 98.34 respectively.

TABLE 8. Performance evaluation of the proposed IoMT-enabled transfer learning model.

Metric	Mild Demented	Moderate Demented	Non Demented	Very Mild Demented	Overall Mean	Overall Std Dev
			Training Results			
Precision	0.9914	0.9792	0.9723	0.9842	0.9818	0.0081
Sensitivity (Recall)	0.9846	0.9689	0.9828	0.9827	0.9798	0.0073
Specificity	0.9939	0.9922	0.9922	0.9967	0.9938	0.0021
Misclassification Rate	0.0086	0.0208	0.0277	0.0158	0.0182	0.0081
F1 Score	0.9880	0.9739	0.9775	0.9834	0.9807	0.0062
Overall Training Accuracy			98.19%			
			Validation Results			
Precision	0.9856	0.9485	0.9382	0.9165	0.9472	0.0289
Sensitivity (Recall)	0.9567	0.9491	0.9508	0.9334	0.9475	0.0099
Specificity	0.9928	0.9925	0.9885	0.9903	0.9910	0.0020
Misclassification Rate	0.0144	0.0515	0.0618	0.0835	0.0528	0.0289
F1 Score	0.9710	0.9488	0.9445	0.9248	0.9473	0.0190
Overall Validation Accuracy			96.06%			

We have compared the performance differences among the dementia classification algorithms under study using paired t-tests and one-way ANOVA The following t-statistics and p-values were obtained from the paired t-tests: Mild Demented vs. Moderate Demented (t-statistic = 6.2906,

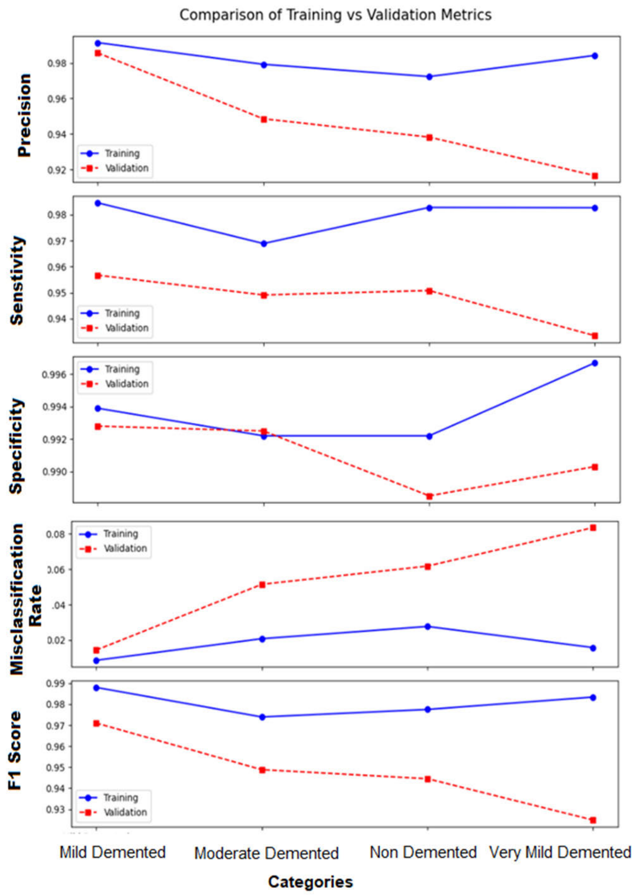

FIGURE 12. Comparison of training and validation metrics.

p-value = 0.0033), Mild Demented vs. Non Demented (t-statistic = 7.0173, p-value = 0.0022), and Mild Demented vs. Very Mild Demented (t-statistic = 4.5416, p-value = 0.0105). These results demonstrated significant differences. Significant differences between the groups were also shown by the ANOVA results (F-statistic = 9.5475, p-value = 0.0008).

Our models perform robustly, as evidenced by the paired t-tests that showed statistically significant differences in performance metrics between the classes, with p-values less than 0.05 for multiple comparisons.

We acknowledge the significance of providing confidence intervals or standard errors for the performance measurements that have been presented. To further aid in understanding the performance variability, we will also give mean and standard deviation metrics surrounding the estimations.

With an F-statistic of 9.5475 and a p-value of 0.0008, the ANOVA findings further validated the overall model performance and confirmed the presence of significant differences among the various groups that were evaluated.

Paired t-tests across each class pair and a one-way ANOVA were used to confirm the statistical significance of the performance variability between dementia classes. The observed performance disparities between classes are statistically significant, as confirmed by the ANOVA's substantial F-statistic (9.5475) and p-value of 0.0008. The robustness of the metrics shown in Table 9 is further supported by this analysis, which also shows how well proposed model differentiates across dementia phases, it presents class wise mean and standard deviation of the model while Figure 13 presents it visual representation.

TABLE 9. Class wise mean and standard deviation using 80/20 train-test split approach of the proposed IoMT-enabled transfer learning model.

Class	Mean	Standard Deviation
Mild Demented	0.9913	0.0006
Moderate Demented	0.9789	0.0008
Non Demented	0.9723	0.0006
Very Mild Demented	0.9844	0.0008

For each of the four dementia classes Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented the mean and standard deviation of proposed model's performance metrics (such as accuracy, precision, and recall) based on five different model runs is presented in Table 9. A single 80/20 train-test split was used for each run, and performance data were separately recorded for every dementia class. In order to provide a trustworthy indicator of central tendency, the mean for each class's metric was calculated by adding up all of the run scores and dividing by the total number of runs. The standard deviation, is determined, which is the square root of the average squared deviations from the mean, to measure the range of values around this mean.

Boxplot, provided in Figure 14 to visualize the distributions of the performance metrics for each class. This provides a clearer understanding of the performance variability among the classes. It shows the minimum, first quartile, median, third quartile, and maximum values for each class illustrates the variety of metrics across runs

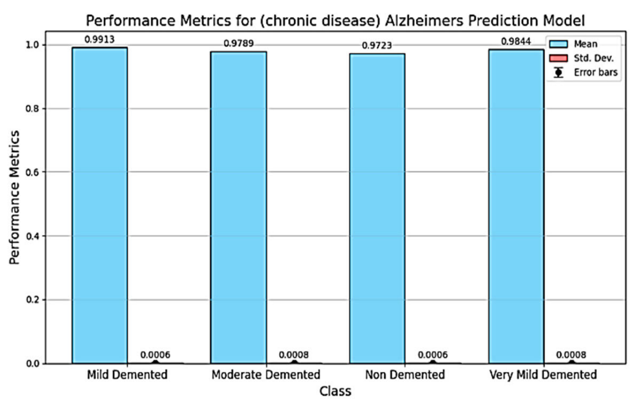

FIGURE 13. Performance metrics for Alzheimer classification model.

In addition to the summary data in Table 9, this plot draws attention to distributional features such as any Skewness and any outliers.

Evaluation with Bootstrapping

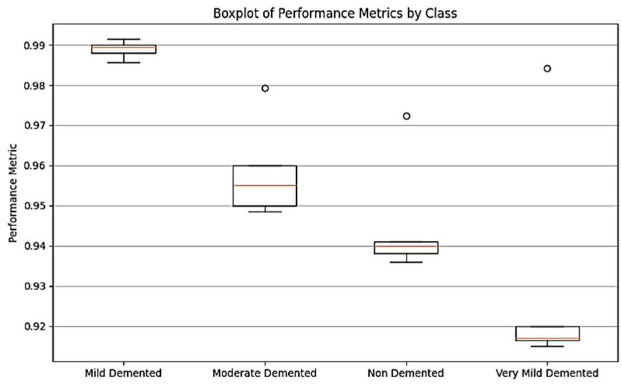

FIGURE 14. Boxplot illustrating class-wise performance metrics of the model using 80/20 train-test split approach.

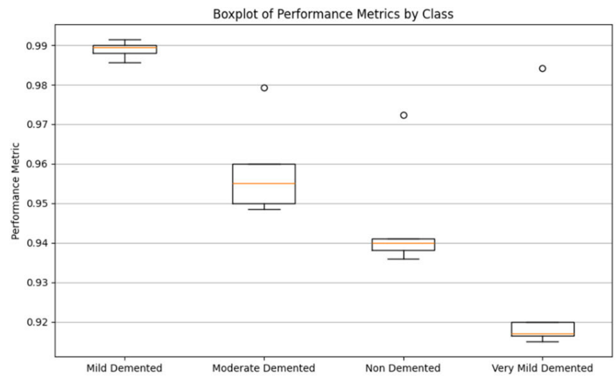

FIGURE 15. Boxplot illustrating class-wise performance metrics of the model with bootstrapping applied.

The mean and variability (standard deviation) for each dementia categorization are clearly summarized by the bootstrapping technique, which also offers important information about performance stability across classes. The mean performance metric for the Mild Demented category is high (0.9889) with a low standard deviation (0.0009), suggesting minimal variability and consistent and dependable performance. With a somewhat lower mean (0.9585) and a standard deviation of 0.0050, the Moderate Demented class exhibits strong performance with minor fluctuation. With a somewhat higher standard deviation (0.0060) and a further decline in mean to 0.9455 for Non Demented. Very Mild Demented group, has the lowest mean (0.9307) and the highest variability (0.0122).

Figure 15 and Table 10 shows bootstrapping to display the model's performance data per class. For each dementia class Mild Demented, Moderate Demented, Non Demented, and Very Mild Demented the distribution of performance metrics (mean and variability) across 1,000 bootstrap samples is displayed in this graphic. With less variability for Mild and Moderate Demented and more variability for Very Mild Demented, the boxplot illustrates performance consistency across classes and sheds light on model stability.

TABLE 10. Class-wise mean and standard deviation of the proposed IoMT-enabled transfer learning model using bootstrapping.

Class	Mean	Standard Deviation
Mild Demented	**0.9889**	0.0009
Moderate Demented	**0.9585**	0.0050
Non Demented	**0.9455**	0.0060
Very Mild Demented	**0.9307**	0.0122

In the training phase, an accuracy of 98.19% was attained overall. The model's validation results showed significantly lower but still impressive performance: 98.56% to 91.65% for precision, 95.67% to 93.34% for sensitivity, and 99.28% to 99.03% for specificity. With percentages of 1.44% for Mild Demented, 5.15% for Moderate Demented, 6.18% for Non-Demented, and 8.35% for Very Mild Demented, misclassification rates were greater than training. The validation's F1 scores were 97.10%, 94.88%, 94.45%, and 92.48%, in that order. This translated into an overall accuracy of 96.06%. These findings highlight how well the IoMT-enabled system diagnoses Alzheimer's disease across a variety of datasets. Accuracy comparison of the proposed IoMT enabled-transfer learning approach and other related work is presented in Table 11.

TABLE 11. Accuracy comparison of the proposed IoMT-enabled transfer learning model.

Ref	Method	Accuracy
[36]	Deep RNN	C index 90%
[37]	Decision Tree, Random Forest, Support Vector Machine, Gradient Boosting, and Voting classifiers	83%
[38]	DNN	85.19%
[39]	Decision Tree, Support Vector Machine,	85%, 83%
[40]	Support Vector Machine	56.1%
[41]	CNN	80%
[42]	Generalized Linear Model	88%
[43]	Support Vector Machine	81.7%
[44]	Support Vector Machine	80-86%
[45]	CNN and RNN	91.33%
[46]	CNN DEMentia NETwork (DEMNET)	84.83 %
[47]	Gaussian process algorithm	-
[48]	DCNN	73.75%
[49]	KNN , Random Forest, SVM	87.39%
[50]	DKPCA + MKSVM	92.5%
[51]	ANFIS Classifier and SVM	81.22%
[52]	DNN	58%
[53]	Logistic Regression	87.1%
[54]	SVM and KNN	85%
[55]	CNN	86.60%
Proposed Model	**Transfer Learning**	**96.06%**

V. CONCLUSION

In conclusion, employing MRI data and after performing its segmentation using U-net, this study presents a deep machine learning model that incorporates transfer learning for early Alzheimer's disease prediction. Our proposed framework uses transfer learning to improve the extraction of spatial attributes and the capturing of temporal correlations from brain pictures by utilizing knowledge from pre-trained models. With a more thorough representation produced by this method, prediction accuracy is increased. The U-net model is trained and MRI images are segmented and then Transfer learning is applied through its use in data preparation, model architecture design, and rigorous training and evaluation procedures, transfer learning highlights the potential of deep machine learning in the diagnosis of Alzheimer. Additionally, the wider advantages of deep machine learning in healthcare are emphasized, especially, in managing the complexity of chronic diseases. Deep learning techniques are particularly useful in medical image processing, as demonstrated by the model's capacity to uncover complex patterns from large and dynamic MRI datasets. Personalized healthcare treatments and early disease prediction are enhanced by the application of transfer learning, which enables better patient outcomes in the treatment of chronic diseases. MATLAB 2020a was used to simulate the proposed IoMT-enabled intelligent system for Healthcare 5.0, which uses an IoMT-based TL model. In the smart healthcare sector, our approach outperformed earlier techniques for predicting Alzheimer's disease, with an accuracy of 96.06%.

The U-Net model is utilized in segmentation to pinpoint and separate critical brain areas affected by Alzheimer's disease, like the cortex and hippocampus. This gives the ResNet-101 classification model a foundational level of interpretability, guaranteeing that predictions about cognitive states are based on significant anatomical features. Still, there is potential for improvement in the model's decision-making process' interpretability. In order to increase transparency and give doctors greater confidence in the model's predictions, the researchers intend to provide visualization tools that emphasize particular regions or qualities that influence classification decisions. ANOVA and paired t-tests are the statistical analysis approaches that are used to determine areas with greater predictive powers and to comprehend the significance of features in categorization. This technique provides insights into the model's decision-making process and emphasizes the significance of particular MRI image regions. The study acknowledges the constraints associated with the size of the dataset, which consists of 6,400 MRI scans used to categorize Alzheimer's disease across different levels of cognitive impairment. Despite the fact that this dataset is deemed tiny for deep learning applications, segmentation techniques were used to improve the quality of the data, maximizing its usefulness. To enhance the model's capacity to identify complex patterns, pertinent regions of interest were separated. Furthermore, it is acknowledged that external validation is crucial for evaluating the model's generalizability across various patient demographics and imaging scenarios. External datasets will be incorporated into future work to provide a more thorough assessment of the model's dependability and performance in actual clinical situations.

Although our model showed great accuracy in identifying the phases of Alzheimer's disease, it is acknowledged that it is crucial to look into the precise characteristics and areas of the brain that affect classification choices. A U-Net model was used for segmentation to improve clinical relevance. This allowed for the detection of important anatomical features in MRI images. This segmentation helps clinicians grasp the model's outputs by reducing noise and irrelevant information while also enabling a sharper visual portrayal of brain disorders.

The possible benefit goes beyond Alzheimer's disease, demonstrating how adaptable these strategies are to support early detection and intervention for a range of chronic diseases. The cooperative integration of cutting-edge deep machine-learning techniques into clinical workflows has enormous potential to transform disease prediction and individualized patient treatment as the field develops.

CONTRIBUTION AND FUTURE WORK

Recent research has already proposed numerous recommendation systems for healthcare. This study significantly contributes to enhancing the healthcare 5.0 by developing an IoMT-enabled model for the accurate prediction of chronic disease like Alzheimer's. The process begins with data collection, followed by preprocessing and segmentation to refine the healthcare dataset. Utilizing transfer learning with deep machine algorithms, the system achieves high accuracy and performs well with larger datasets. The developed IoMT-enabled intelligent system for healthcare 5.0, featuring an IoMT-enabled transfer learning approach, predicts Alzheimer's disease with an overall accuracy of 96.06%. Future enhancements will focus on early detection of preclinical Alzheimer's disease and mild cognitive impairment, aiming to generalize the model by incorporating additional imaging modalities. In order to provide a more thorough assessment, we intend to add more MRI scans from other outside sources to our dataset in further work. It is acknowledged, although, that more sophisticated explainability techniques, like Grad-CAM (Gradient-weighted Class Activation Mapping) and SHAP (SHapley Additive exPlanations), may improve our existing approaches and offer more profound insights into the model's decision-making processes. Future studies will investigate these advanced approaches in order to clarify the model's interpretability and enhance its therapeutic application.

This will increase the model's usefulness in actual clinical settings by enabling us to validate it across various populations and medical facilities.

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