

**Master Thesis Proposal**

**Customer support using Al technologies.**

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**Research Area**

AI tools – Customer support system

**Abstract**

This project proposes the implementation of an AI-powered system to enhance customer support operations by improving response times and customer satisfaction while reducing the manual handling of routine inquiries.

The initiative will be deployed in five strategic phases: Requirement Gathering, Data Preparation and Model Development, System Integration, Deployment, and Evaluation.

Key outcomes include a 30% reduction in response times and automation of 50% of routine inquiries, leading to a 20% increase in customer satisfaction scores.

Through this project, the system will automate responses and categorize tickets efficiently, transforming customer interactions into personalized and satisfying experiences while streamlining support operations.

**Introduction**

Today's customer service landscape is rapidly evolving, with Artificial Intelligence (AI) at the heart of this transformation. As businesses expand, they often find themselves grappling with an increasing volume of customer inquiries. Traditional support systems like CRM (Customer Relationship Management) can falter under this pressure, leading to slower response times and a decline in the quality of service. Such shortcomings can significantly dampen customer satisfaction.

However, the integration of AI into the customer support systems is not merely a remedy for efficiency; it's a gateway to redefining customer interactions. By harnessing AI, organizations have the opportunity to not only streamline their processes but also to add a layer of personal touch to their communications, fundamentally enhancing the overall customer experience AI, particularly in the context of CRM, leverages machine learning (ML) and deep learning (DL) methods to extract insights from data, identify patterns, and make decisions with minimal human oversight (Kumar et al., 2020).

Also, the modern language generation model ChatGPT, created by Open Artificial Intelligence (AI), with the ability to “generate human-like text” (Aydın & Karaarslan, 2022) is recognized for its capacity to comprehend context and produce pertinent content. This model is built on the transformer architecture, which enables it to process massive volumes of data and produce text that is both cohesive and illuminating. Service is a crucial component everywhere as it provides the basis for establishing client rapport and offering aid and support.

Businesses may enhance customer experience by using ChatGPT's potential for assistance in any sector. The application of ChatGPT for customer support has been one of the most significant advances in recent years. This strategic adoption of AI technologies paves the way for more responsive, intuitive, and personalized service, transforming how businesses connect with their customers.

**Problem Definition**

One of the persistent challenges in Customer Relationship Management (CRM) is providing personalized, timely responses to customer inquiries. Traditionally, CRM systems have been effective in managing customer data but often fall short in delivering real-time, context-aware interactions. This can lead to customer dissatisfaction, as modern consumers expect quick and tailored services based on their previous interactions and preferences.

Many organizations struggle with integrating their CRM systems across various departments. This often results in data silos where valuable customer information is trapped in one part of the business and inaccessible to others, hindering effective communication and service delivery (Ngelyaratan & Soediantono 2022).

Scalability Issues, as businesses grow, the volume of customer interactions increases exponentially. Traditional CRM systems may not scale efficiently, leading to slower system performances and increased waiting times for customers.

AI technologies, particularly those using machine learning algorithms, can analyze vast amounts of data from CRM systems to identify patterns and preferences of individual customers. ChatGPT can leverage this data to generate personalized responses automatically, ensuring that each customer feels understood and valued. This not only improves the customer experience but also enhances customer loyalty and retention (Libai et al., 2020)

Real-Time Response and Interaction, ChatGPT can process and respond to customer queries in real time, significantly reducing waiting times. With its advanced natural language processing capabilities, it can understand and engage in human-like conversations, providing immediate and relevant assistance to customers. This capability is crucial for maintaining high customer satisfaction levels in a fast-paced market environment (J. Paul, A. Ueno, C. Dennis 2023)

ChatGPT can be integrated into existing CRM systems to bridge the gap between data silos within an organization. It can pull information from various sources to provide a comprehensive view of the customer, which is accessible to all relevant departments. This holistic approach ensures that all interactions with a customer are informed and consistent across all touchpoints (A.S. George, A.H. George 2023).

AI-driven solutions like ChatGPT are highly scalable, capable of handling an increasing number of interactions without additional significant resources. This makes it an ideal solution for growing businesses that need to manage large volumes of customer interactions efficiently. Moreover, the automation of routine inquiries frees human agents to handle more complex issues, enhancing overall productivity and service quality. By addressing these core CRM issues effectively, AI and ChatGPT not only streamline customer relationship management processes but also transform them into more customer-centric systems that can adapt and evolve in response to changing customer needs (Abid Haleem, Mohd Javaid, Ravi Pratap Singh 2024)

**Dataset**

This section describes a collection of public datasets in different literature that are used in the field of brain damage diseases. Some literature has also used data collected from patients of various hospitals.

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| **Dataset Name** | **Link** | **Biomarker** | **Size & Samples** | **Limitations** |
| Alzheimer's Disease Neuroimaging Initiative (ADNI) | [ADNI |  ACCESS DATA (usc.edu)](https://adni.loni.usc.edu/data-samples/access-data/) | Clinical  Genetic  MRI  Positron Emission Tomography (PET)  Biospecimen | 150TB  data samples | ADNI is a large and complex dataset, which can make it challenging to navigate and analyze |
| Kaggle Alzheimer's classification dataset (KACD) | [Dataset\_Alzheimer (kaggle.com)](https://www.kaggle.com/datasets/yasserhessein/dataset-alzheimer?resource=download) | MRI | 6400 images | Not all participants have complete longitudinal data, which can limit the analysis of certain time-dependent phenomena. |
| Parkinson's Progression Markers Initiative (PPMI) | <https://www.ppmi-info.org/access-data-specimens/download-data> | Clinical  Imaging  Omics  Genetic  Sensor  Biomarker | 17.5TB  data samples | Not all participants have neuroimaging data for all time points, which can limit the analysis of certain imaging-related phenomena. |
| Open Access Series of Imaging Studies (OASIS) | https://www.oasis-brains.org/ | MRI, PET imaging, neuropsychological testing, and clinical data | 416 subjects  140,000 images | The OASIS dataset faces challenges in data transfer, entry, signposting, transparency, and inconsistencies in results, necessitating further research for its value in patient outcomes and quality improvement. |

**Related Work**

There exist several studies that focused on the diagnosis of brain tumors especially the Parkinson and the Alzheimer diseases. B. Chen et al. ‎[8] proposed Diffusion Tensor Imaging (DTI) indices serve as the foundation for a ML model for PD-MCI detection. The XGBoost model that combined the intra- and intervoxel indices performed the best with a 91.67% accuracy rate, gradient boosting decision tree models that use intra- and intervoxel DTI indices successfully identify MCI in PD. FSL 5.0.9 and PANDA (Pipeline for Analysing briN Diffusion ages) were used for DTI data preparation and atlas-based analysis (ABA). Format conversion, mask creation and cropping, head motion and eddy correction, and spatial registration were among the preprocessing procedures. They plan to investigate more ways to use more features to increase classification accuracy in the future.

‌A. A. Vijayakumari et al. ‎[9] proposed a structural MRI-based biomarker to forecast how quickly motor symptoms would worsen in the early phases of Parkinson's disease. From the Parkinson's Progression Markers Initiative database (PPMI), 120 healthy controls and 88 PD patients were included in the study. They used a support vector machine classifier to classify patients with 89% accuracy into comparatively slower and faster progress groups. Using regions of interest (ROIs) unique to each non-motor symptom, they will investigate in the future whether the multivariate method (MD) can predict non-motor symptoms.

Al-Adhaileh et al.‎[10] proposed a diagnostic system for AD using deep neural network techniques. Deep neural network techniques (AlexNet and Restnet50) achieved superior performance in the classification and recognition of AD. The proposed method can help improve computer-aided diagnostic methods for AD. The AlexNet model achieved an accuracy of 94.53%, and The Restnet50 model achieved an accuracy of 58.07%. The Future work can focus on expanding the dataset and evaluating the model on a larger scale and the proposed method can be further improved by incorporating more advanced DL techniques.

R. A. Hazarika et al.‎[11] proposed a hybrid approach using a combination of LeNet and AlexNet models for the classification of AD using brain MRI scans. The model achieved an overall performance rate of 93.58%. The future work of this paper is to acquire more data from different databases to compare and improve results and explore the use of advanced DNN concepts, such as the Dense-block notion, to improve model performance.

M. Mamun et al.‎[19] proposed DL-based models for Alzheimer's detection using MRI images and they used Four models used: CNN, ResNet101, DenseNet121, VGG16.The dataset used in the study consists of 6219 MRI images. The dataset includes images of both demented and non-demented brains. In the future, we may use newly developed DL models and pre-trained deep architectures for more accurate results for Alzheimer's detection.

M. Orouskhani et al.‎[20] proposed a conditional deep Triplet network to get around the ML difficulties' data shortage. Next, the model is used to identify brain MRIs and forecast a four-class categorization issue for AD. Our model's fundamental network is based on the VGG-16. The OASIS dataset was used to run the simulation, and the results were compared to the six state-of-the-art methods currently in use.

G. Pahuja et al.‎‎[21] proposed That is currently being considered to employ multi-modal features to increase the accuracy of PD diagnosis. Using biological and neuroimaging variables as the dataset, they employed two DL-based frameworks—feature-level and modal-level—to classify the participants into PD and healthy groups. In the feature-level and modal-level frameworks, CNN's highest accuracy is 93.33% and 92.38%, respectively. The findings support the use of the multi-modal feature-based strategy for dividing the participants into PD and healthy groups.

S. Desai et al. ‎[22] they used MRI examine pictures to recognize Parkinson’s illness is taken from Parkinson’s progression markers initiative (PPMI). They implemented ML techniques like decision tree classification, support vector machine (SVM), naïve bayes classification, KNN classification and XGBoost classifier. They got the highest accuracy for the support vector machine about 86%. the future, implementation of DL techniques like CNN can also be done which can give us more accurate results for the detection of PD.

**Related Work Summary**

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| **References** | **Datatype** | **Training Model** | **Accuracy** | **Dataset** |
| ‎  B. Chen et al. ‎[8]  2023 | MRI | XGBoost | 91.67% | FSL (FMRIB Software Library) PANDA (Pipeline for Analysing braiN Diffusion imAges) |
| A. A. Vijayakumari et al. ‎[9]  2023 | MRI-based biomarker | SVM | 89% | PPMI |
| Al-Adhaileh et al. ‎[10]  2022 | MRI | AlexNet  Restnet50 | 94.53%  58.07% | Kaggle Alzheimer's classification dataset (KACD) |
| R. A. Hazarika et al. ‎[11]  2023 | MRI | DenseNet-121  LeNet and AlexNet | 86.55%  93.58%. | ADNI |
| M. Mamun et al. ‎[19]  2022 | MRI | CNN | 97.60% | Alzheimer's Dataset |
| M. Orouskhani et al. ‎[20]  2022 | MRI | Conditional Triplet- VGG | 99.4% | OASIS |
| G. Pahuja et al. ‎[21]  2022 | MRI | CNN | 93.33% | PPMI |
| S. Desai et al. ‎[22]  2022 | MRI | SVM | 86% | PPMI |

**Research Objective**

The objective of this study is to develop a DL-based classification model for the early detection and classification of brain ageing disorders, including AD and PD using different datasets. The system will be designed to determine the severity of the diseases using classification techniques. The study will evaluate the performance of the system using various metrics and compare it with other traditional diagnostic methods. The results of this study will help improve the accuracy and speed of diagnosis, allowing for earlier intervention and better patient outcomes.

This can be decomposed into the following sub-objectives:

* Selecting and implementing proper algorithms from the recent literature for detecting brain aging disorders.
* Evaluating the selected algorithms based on metrics such as accuracy, precision, and recall.
* Modifying the selected algorithms or proposing and designing new algorithms to overcome their drawbacks.
* Compare the obtained result with the other results obtained before for brain aging disorders.

**Research Plan**

Data Collection: PPMI dataset for Parkinson and ANDI dataset for Alzheimer which are providing a range of data types and information to advance research in these neurodegenerative conditions. Those datasets are available online which makes it easy to use.

Data Preprocessing: Data preprocessing techniques, like normalization and dimensionality reduction, are used to prepare the data for classification algorithms, ensuring it is in a suitable format for analysis.

Feature Extraction: Classification models start by extracting relevant features from data sources like brain imaging, genetic information, and clinical records. These features can include brain volume, biomarkers, and cognitive test scores.

Model Training: Classification models, such as Support Vector Machines (SVMs), Convolution Neural Networks or Long Short-Term Memory (LSTM), are trained on labeled datasets. These models learn to classify individuals into different categories, like healthy or at-risk for brain aging disorders, based on the extracted features.

Validation and Testing: The trained models are validated and tested using separate datasets to assess their accuracy and generalization capabilities. This step ensures the model's reliability in early detection.

Predictive Biomarkers: Classification models can identify predictive biomarkers or patterns in the data that are indicative of brain aging disorders. These biomarkers aid in the early identification of individuals at risk.

Continuous Monitoring: Classification techniques can be applied to monitor changes in brain health over time, allowing for continuous assessment and early intervention as necessary.

**References**

Kumar, V., Ramachandran, D., Kumar, B., (2020). Influence of new-age technologies on marketing: a research agenda. J. Bus. Res. https://doi.org/10.1016/j. jbusres.2020.01.007

Aydın, Ö., Karaarslan, E. (2022). OpenAI ChatGPT Generated Literature Review: Digital Twin in Healthcare . In Ö. Aydın (Ed.), Emerging Computer Technologies 2 (pp. 22-31). http://dx.doi.org/10.2139/ssrn.4308687

D. Ngelyaratan and D. Soediantono, Customer relationship management (CRM) and recommendation for implementation in the defense industry: A Literature Review, Journal of IndustrialEngineering & Management Research, Vol. 3, No. 3, pp. 17-34, (2022). https://doi.org/10.7777/jiemar.v3i3.279

Libai et al., (2020) B. Libai, Y. Bart, S. Gensler, C.F. Hofacker, A. Kaplan, K. Kötterheinrich, E.B. KrollBrave new world? On AI and the management of customer relationships

August 2020 J. Interact. Mark., 51 (2020), pp. 44-56, https://doi.org/10.1016/j.intmar.2020.04.002

J. Paul, A. Ueno, C. Dennis, ChatGPT and consumers: benefits, pitfalls and future research agenda, Int J Consum Stud, 47 (4) (2023), pp. 1213-1225, https://doi.org/10.1111/ijcs.12928

A.S. George, A.H. George, A review of ChatGPT AI's impact on several business sectors

Partners Universal International Innovation Journal, 1 (1) (2023), pp. 9-23, https://doi.org/10.5281/zenodo.7644359

Abid Haleem, Mohd Javaid, Ravi Pratap Singh, Exploring the competence of ChatGPT for customer and patient service management (2024), https://doi.org/10.1016/j.ipha.2024.03.002

1. M. Nilashi *et al.*, “Early diagnosis of Parkinson’s disease: A combined method using deep learning and neuro-fuzzy techniques,” *Computational Biology and Chemistry*, vol. 102, p. 107788, Feb. 2023, doi: <https://doi.org/10.1016/j.compbiolchem.2022.107788>.
2. Mahmood, M. Mehroz Khan, M. Imran, O. Alhajlah, H. Dhahri, and T. Karamat, “End-to-End Deep Learning Method for Detection of Invasive Parkinson’s Disease,” *Diagnostics*, vol. 13, no. 6, p. 1088, Mar. 2023, doi: <https://doi.org/10.3390/diagnostics13061088>.
3. L. Baecker, R. Garcia-Dias, S. Vieira, C. Scarpazza, and A. Mechelli, “Machine learning for brain age prediction: Introduction to methods and clinical applications,” *EBioMedicine*, vol. 72, p. 103600, Oct. 2021, doi: <https://doi.org/10.1016/j.ebiom.2021.103600>.
4. T Illakiya and R Karthik, “Automatic Detection of Alzheimer’s Disease using Deep Learning Models and Neuro-Imaging: Current Trends and Future Perspectives,” vol. 21, no. 2, pp. 339–364, Mar. 2023, doi: <https://doi.org/10.1007/s12021-023-09625-7>.
5. H. A. Helaly, M. Badawy, and A. Y. Haikal, “Deep Learning Approach for Early Detection of Alzheimer’s Disease,” *Cognitive Computation*, Nov. 2021, doi: <https://doi.org/10.1007/s12559-021-09946-2>.
6. W. Wang, J. Lee, F. Harrou, and Y. Sun, “Early Detection of Parkinson’s Disease Using Deep Learning and Machine Learning,” *IEEE Access*, vol. 8, pp. 147635–147646, 2020, doi: <https://doi.org/10.1109/access.2020.3016062>.
7. Y. Du, Z. Fu, and V. D. Calhoun, “Classification and Prediction of Brain Disorders Using Functional Connectivity: Promising but Challenging,” *Frontiers in Neuroscience*, vol. 12, Aug. 2018, doi: <https://doi.org/10.3389/fnins.2018.00525>.
8. B. Chen *et al.*, “Detection of mild cognitive impairment in Parkinson’s disease using gradient boosting decision tree models based on multilevel DTI indices.,” vol. 21, no. 1, pp. 310–310, May 2023, doi: <https://doi.org/10.1186/s12967-023-04158-8> .
9. A. A. Vijayakumari, H. H. Fernandez, and B. L. Walter, “MRI-based multivariate gray matter volumetric distance for predicting motor symptom progression in Parkinson’s disease,” *Scientific Reports*, vol. 13, no. 1, Oct. 2023, doi: <https://doi.org/10.1038/s41598-023-44322-0> .
10. Al-Adhaileh, M. H. (2022). Diagnosis and classification of Alzheimer’s disease by using a convolution neural network algorithm. *Soft Computing*, *26*(16), 7751–7762. <https://doi.org/10.1007/s00500-022-06762-0>.
11. R. A. Hazarika *et al.*, “An Approach for Classification of Alzheimer’s Disease Using Deep Neural Network and Brain Magnetic Resonance Imaging (MRI),” *Electronics*, vol. 12, no. 3, p. 676, Jan. 2023, doi: <https://doi.org/10.3390/electronics12030676>.
12. F. N. Emamzadeh and A. Surguchov, “Parkinson’s Disease: Biomarkers, Treatment, and Risk Factors,” *Frontiers in Neuroscience*, vol. 12, no. 612, Aug. 2018, doi: <https://doi.org/10.3389/fnins.2018.00612>.
13. Ö. Eskidere, F. Ertaş, and C. Hanilçi, “A comparison of regression methods for remote tracking of Parkinson’s disease progression,” *Expert Systems with Applications*, vol. 39, no. 5, pp. 5523–5528, Apr. 2012, doi: <https://doi.org/10.1016/j.eswa.2011.11.067>.
14. X. Zhao, C. K. E. Ang, U. R. Acharya, and K. H. Cheong, “Application of Artificial Intelligence techniques for the detection of Alzheimer’s disease using structural MRI images,” *Biocybernetics and Biomedical Engineering*, vol. 41, no. 2, pp. 456–473, Apr. 2021, doi: <https://doi.org/10.1016/j.bbe.2021.02.006>.
15. I. Beheshti, H. Demirel, and H. Matsuda, “Classification of Alzheimer’s disease and prediction of mild cognitive impairment-to-Alzheimer’s conversion from structural magnetic resource imaging using feature ranking and a genetic algorithm,” *Computers in Biology and Medicine*, vol. 83, pp. 109–119, Apr. 2017, doi: <https://doi.org/10.1016/j.compbiomed.2017.02.011>.
16. D. Lenzi *et al.*, “Single domain amnestic MCI: A multiple cognitive domains fMRI investigation,” *Neurobiology of Aging*, vol. 32, no. 9, pp. 1542–1557, Sep. 2011, doi: <https://doi.org/10.1016/j.neurobiolaging.2009.09.006>.
17. N. Amoroso *et al.*, “Deep learning reveals Alzheimer’s disease onset in MCI subjects: Results from an international challenge,” *Journal of Neuroscience Methods*, vol. 302, pp. 3–9, May 2018, doi: <https://doi.org/10.1016/j.jneumeth.2017.12.011>.
18. S. Dubey. 2022. Alzheimer's Dataset (4 class of Images). [ online ] Kaggle.com. Available at: [Alzheimer's Dataset ( 4 class of Images) (kaggle.com)](https://www.kaggle.com/datasets/tourist55/alzheimers-dataset-4-class-of-images) [Accessed 1 September 2022].
19. M. Mamun, Siam Bin Shawkat, Salim Ahammed, Md Milon Uddin, Md Ishtyaq Mahmud, and Asm Mohaimenul Islam, “Deep Learning Based Model for Alzheimer’s Disease Detection Using Brain MRI Images,” Oct. 2022, doi: <https://doi.org/10.1109/uemcon54665.2022.9965730>.
20. M. Orouskhani, C. Zhu, S. Rostamian, F. Shomal Zadeh, M. Shafiei, and Y. Orouskhani, “Alzheimer’s disease detection from structural MRI using conditional deep triplet network,” *Neuroscience Informatics*, vol. 2, no. 4, p. 100066, Dec. 2022, doi: <https://doi.org/10.1016/j.neuri.2022.100066>.
21. G. Pahuja and B. Prasad, “Deep learning architectures for Parkinson’s disease detection by using multi-modal features,” *Computers in Biology and Medicine*, vol. 146, p. 105610, Jul. 2022, doi: <https://doi.org/10.1016/j.compbiomed.2022.105610>.
22. S. Desai, D. Mehta, Vijay Dulera, and Hitesh Chhikaniwala, “Parkinson’s Disease Detection Using Machine Learning,” *Lecture notes in networks and systems*, pp. 43–58, Jan. 2022, doi: <https://doi.org/10.1007/978-981-19-2894-9_4>.
23. W. H. Organization, “Launch of WHO’s Parkinson disease technical brief,” 2024.
24. S. B. Hassen, M. Neji, Z. Hussain, A. Hussain, A. M. Alimi, and M. Frikha, “Deep learning methods for early detection of Alzheimer’s disease using structural MR images: a survey,” *Neurocomputing*, vol. 576, p. 127325, Apr. 2024, doi: <https://doi.org/10.1016/j.neucom.2024.127325>.
25. M. R. Ahmed, Y. Zhang, Z. Feng, B. Lo, O. T. Inan and H. Liao, "Neuroimaging and Machine Learning for Dementia Diagnosis: Recent Advancements and Future Prospects," in IEEE Reviews in Biomedical Engineering, vol. 12, pp. 19-33, 2019, doi: <http://10.1109/RBME.2018.2886237>.
26. R. Ganotra, S. Dora, and S. Gupta, “Identifying brain regions contributing to Alzheimer’s disease using self-regulating particle swarm optimization,” *International Journal of Imaging Systems and Technology*, Jun. 2020, doi: <https://doi.org/10.1002/ima.22458>.
27. “FSL - FslWiki,” *fsl.fmrib.ox.ac.uk*. https://fsl.fmrib.ox.ac.uk/.
28. “NITRC: PANDA: a pipeline tool for diffusion MRI: Tool/Resource Info,” *www.nitrc.org*. http://www.nitrc.org/projects/panda/.