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AlzBuddy: Integrating Edge-AI Object Detection And Geofencing For Cognitive Therapy And Safety In Dementia Care

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Abstract
The global rise in Alzheimer's disease and dementia presents a critical challenge for healthcare systems, placing an immense burden on caregivers to ensure patient safety and sus- tain cognitive function. While assistive technologies exist, current solutions often remain fragmented offering either passive track- ing or static screen-based games and lack interactive engagement with the patient's physical environment. This paper presents AlzBuddy, a comprehensive AI-powered mobile application that digitizes and optimizes safety monitoring and cognitive therapy for dementia care. The system employs an on-device machine learning pipeline using TensorFlow.js and the COCO-SSD model to power a novel" Scavenger Hunt" game, which gamifies object recognition to stimulate memory retention in the user's real- world surroundings. A key contribution is the integration of GPS- based geofencing algorithms, which define virtual safe zones and trigger low-latency alerts to prevent wandering. The platform further integrates Natural Language Processing (NLP) for per- sonalized voice-guided task assistance and Reminiscence Therapy tools for emotional support. By merging physical-digital cognitive exercises with robust safety protocols, AlzBuddy enhances patient autonomy while significantly alleviating caregiver stress. System validation demonstrates high accuracy in object detection and reliable alert generation, highlighting the potential of accessible mobile technology to transform dementia care.

Index Terms: *Alzheimer's Disease, Object Detection, Scav- enger Hunt, TensorFlow.js, Geofencing, Reminiscence Therapy, Assistive Technology.*

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I. Introduction

Background and Motivation

The rising global burden of chronic neuro degenerative disorders, particularly Alzheimer's disease (AD), continues to pose significant challenges for healthcare systems, with dementia cases expected to triple by 2050 [1]. Conventional caregiving practices are increasingly limited by the need to manage patients' physical safety-most critically the risk of wandering while simultaneously providing sustained cognitive stimulation to mitigate functional decline. Existing therapeutic pathways depend largely on pharmacological treatment or extensive human supervision, both of which place consider- able strain on medical resources and impose emotional and logistical pressures on family caregivers [2].

In recent years, non-pharmacological approaches such as Reminiscence Therapy and cognitive gamification have gained prominence for their demonstrated ability to enhance patient autonomy and overall quality of life [5]. Despite their clinical value, the practical integration of these methods into everyday care remains inconsistent. Many Mobile Health (mHealth) applications provide only isolated capabilities, offering either passive monitoring or limited, static cognitive exercises that fail to reflect the patient's dynamic real-world environment [4].

Advances in Artificial Intelligence (AI) and Internet of Things (IoT) technologies present an opportunity to address these limitations through more adaptive, context-aware sys- tems. Emerging techniques in on-device machine learning, geofencing, and real-time sensing enable privacy-preserving monitoring and interactive therapeutic experiences that were previously infeasible on consumer-grade devices [3]. Mo- tivated by this technological convergence, our work aims to develop a unified mobile platform that integrates object detection, natural language processing, and location-aware services to enhance both safety and cognitive reinforcement. The proposed system seeks not only to support continuous su- pervision but also to promote memory reconstruction through gamified interactions embedded within the patient's physical surroundings.

Problem Statement

Despite the proliferation of mobile health (mHealth) ap- plications for dementia care, the primary barrier to effective, home-based management remains the absence of a unified, intelligent, and accessible digital ecosystem capable of ad- dressing both physical safety and cognitive rehabilitation. Existing solutions often lack the necessary integration of sensory perception and context-awareness. Key shortcomings identified in current assistive technologies include:

1) Fragmented Care Ecosystems:Current market solu- tions are typically siloed, offering either passive GPS tracking or static brain games, but rarely both. This fragmentation forces caregivers to manage multiple dis- jointed applications, introducing friction and reducing the likelihood of consistent adoption for holistic care [3].
2) **Passive Cognitive Engagement:**Traditional cognitive therapy apps rely heavily on 2D screen-based interactions that isolate the patient from their physical environment. These systems lack the capability for reality-based engagement, failing to stimulate the neural pathways associated with object recognition and spatial navigation in the real world [5].
3) **Hardware-Dependent Safety Mechanisms:**Safety monitoring solutions are frequently tethered to specialized hardware or wearable. These devices often suffer from limited battery life or user non-compliance (e.g., patients removing uncomfortable devices), resulting in critical safety blind spots during wandering events [2].
4) **Static, Impersonal Interaction:**Most reminder systems utilize generic, text-based notifications that fail to account for the user's cognitive state or need for auditory reinforcement. They lack the data-driven adaptability to reconstruct memory through personalized, voice-guided associations with familiar people and objects.

This project formally addresses this technological gap by focusing on the development of an integrated mobile framework capable of automating safety monitoring through geofencing, enhancing cognitive therapy through AI-driven object detection, and personalizing daily assistance. The proposed AlzBuddy system is designed to function as an intelligent "compassionate companion," replacing static, disjointed tools with a cohesive, logic-driven application that improves patient autonomy and caregiver peace of mind.

C. Objectives and Scope

AlzBuddy aims to deliver a comprehensive, end-to-end, AI-driven assistive platform that ensures the safest and most engaging environment for dementia care while reducing the supervision burden on caregivers. The specific objectives are:

1) **Secure Multi-Role Interface with Intelligent Assistance:** To implement robust role-based access control that distinguishes between "Caregiver" and "Patient" modes. The patient interface is architected to minimize cognitive load through high-contrast visuals and simplified navigation, ensuring usability for individuals with declining motor and cognitive skills.
2) **Active Cognitive Stimulation via Computer Vision:** To develop a novel "Scavenger Hunt" game module using on-device machine learning (TensorFlow.js). The objective is to move beyond passive screen tapping by requiring users to identify and interact with physical household objects, thereby stimulating neural pathways associated with object recognition and spatial awareness.
3) **Real-Time Safety Monitoring and Geofencing:**To design a low-latency GPS tracking algorithm that establishes virtual "Safe Zones." The system aims to autonomously detect wandering events using the Haversine formula and trigger instant, multi-channel alerts (SMS and Push Notifications) to caregivers, ensuring rapid intervention.
4) **Digital Memory Reconstruction:**To digitize Reminiscence Therapy through a personalized multimedia module. This involves creating an interactive family album where visual stimuli (photos) are augmented with Text-to-Speech (TTS) audio descriptions, helping patients reconstruct personal narratives and reinforce recognition of loved ones.
5) **Universal Accessibility:**To architect the platform with native multilingual support and voice-first interaction capabilities, ensuring the solution is inclusive for diverse populations and accessible to elderly users with varying levels of digital literacy.

The research scope encompasses the design, full-stack implementation, and empirical validation of these integrated AI and safety modules, evaluating their latency, detection accuracy, and usability within a home-care context.

D. Overview of Methods

The AlzBuddy framework employs a unified, cross-platform mobile architecture integrated with on-device machine learning to deliver automated intelligence for both safety monitoring and cognitive engagement. The methodology consists of multiple coordinated layers, described as follows:

1) **System Architecture:** The application utilizes a scalable React Native framework (Expo SDK 54) to ensure high responsiveness and cross-platform compatibility (iOS and Android). Application state is managed via the React Context API for efficient data flow across modules. Data persistence is handled through AsyncStorage, a local, unencrypted, asynchronous, persistent, key-value storage system, ensuring user data privacy by keeping sensitive information (family photos, emergency contacts) on the device.
2) **Machine Learning and Vision Pipeline:** The cognitive engagement layer leverages a fully on-device computer vision workflow built with TensorFlow.js.
   - **Image Preprocessing:** Images captured through the `CameraView` component are processed using the `expo-image-manipulator` library. Inputs are resized to a standardized width (e.g., 300 px) to optimize tensor conversion and reduce inference time.
   - **Object Detection Model:** Preprocessed tensors are passed into the COCO-SSD detector, which generates bounding box predictions and object class labels with confidence scores. This pipeline powers the interactive "Scavenger Hunt" module, enabling real-time matching of detected household objects with caregiver-defined targets.
3) **Algorithmic Safety Layer:** The safety subsystem implements a deterministic geolocation algorithm to support continuous monitoring.
   - **Geofencing Logic:** Background GPS polling is performed using `expo-location` and `expo-task-manager`. The Haversine formula

computes the user's distance from a predefined safe-zone centroid to detect deviations.
- **Adaptive Alerting:** Upon exceeding the configured radius threshold, the system triggers a multi-modal alert sequence, dispatching local push notifications via `expo-notifications` and SMS messages through `expo-sms`.

4) **Integration and Voice Interface:** All functional modules are integrated using standardized Expo APIs. The voice-first interface incorporates `expo-speech` for text-to-speech synthesis and `@react-native-voice/voice` for speech recognition, enabling hands-free interaction suitable for elderly users.
5) **Operational Reliability and Privacy:** The system is architected to operate with offline capability, minimizing dependence on cloud-based communication while preserving user privacy. On-device computation ensures that cognitive tasks, object recognition, and safety evaluation can be performed without transmitting sensitive data externally.

This integrated methodology establishes the empirical foundation for delivering real-time, context-aware assistance within home-care environments, ensuring the privacy, reliability, and adaptability essential for dementia-focused healthcare applications.

E. Paper Organization

The remainder of this paper is structured as follows: Section II presents the **Related Work and Literature Review**, examining existing assistive technologies for dementia and positioning AlzBuddy within the current mobile health (mHealth) landscape. Section III describes the **Methodology and Proposed System**, detailing the system architecture, the AI-driven Scavenger Hunt game module utilizing TensorFlow.js, and the geofencing safety algorithms. Section IV presents **Results and Discussion**, providing empirical validation of the object detection accuracy and alert latency. Finally, Section V concludes with findings and outlines future research directions, including wearable integration and predictive behavioral modeling.

II. Related Work

A. Summary of Existing Research

Research in dementia care has progressed from gamified social platforms to sophisticated AI and IoT ecosystems. Early interventions utilizing gamification aimed to boost engagement but often struggled to sustain long-term interest in patients with advancing cognitive decline. More recent innovations have leveraged Artificial Intelligence and IoT to automate monitoring; for instance, conversational AI agents and wearable trackers have been developed to provide symptom alerts and location tracking. However, these hardware-dependent solutions frequently encounter barriers such as high implementation costs, limited battery life, and user non-compliance regarding wearable devices.

B. Comparison of Previous Methods.

To contextualize the proposed solution, we evaluate several prominent assistive technologies for dementia care:

1) **Gamified Social Platforms (e.g., CAREGIVERPRO-MMD):** These platforms focus on cognitive rehabilitation through social interaction and serious games. While effective for patients with Mild Cognitive Impairment (MCI), they often lack physical safety monitoring features such as geofencing. Furthermore, studies indicate that engagement levels drop significantly as dementia progresses, as screen-only interactions fail to connect patients with their physical environment.
2) **Wearable & IoT Solutions (e.g. SafeSteps):** Systems utilizing smartwatches or dedicated IoT trackers provide robust outdoor localization and biometric monitoring. However, their reliance on specialized hardware introduces significant barriers: high implementation costs, frequent battery charging requirements, and "device abandonment," where patients refuse to wear uncomfortable accessories. Additionally, they rarely offer integrated cognitive therapy features.
3) **Mobile Tracking Applications (e.g., Alzimio):** Apps like Alzimio popularized GPS-based geofencing on standard smartphones. While accessible, they typically lack indoor navigation capabilities and do not integrate therapeutic modules like reminiscence therapy. Their utility is often limited to passive tracking rather than active assistance.
4) **Conversational AI Agents:** Recent innovations in NLP-based chatbots provide medication reminders and emotional support. However, these systems often function as standalone tools without integration into safety protocols or family-based memory reconstruction, limiting their effectiveness in holistic care scenarios.

TABLE I: Comparison of Existing Assistive Systems vs. AlzBuddy

System	Safety Features	Cognitive Therapy	Key Limitation
Alzimio [3]	GPS Geofencing	None	Relies on GPS; ineffective indoors.
SafeSteps	GPS & Vitals	None	High battery drain; requires wearable hardware.
CAREGIVER PRO-MMD [7]	None	Social Games	Screen-only; low engagement in later stages.
AlzBuddy (Proposed)	**Geofencing & Alerts**	**AI Scavenger Hunt**	**None (Integrated Mobile Solution)**

C. Identified research gap

Despite the advancements in assistive technologies for dementia, **a significant disconnect remains between physical safety monitoring and active cognitive rehabilitation.** Current market solutions are largely fragmented; wearable devices provide robust outdoor tracking but suffer from high costs, limited battery life, and user non-compliance, while mobile applications often function as passive trackers lacking indoor navigation or therapeutic engagement. Furthermore, existing cognitive intervention tools are predominantly screen-based, failing to stimulate the neural pathways associated with real-world object recognition and spatial awareness essential for maintaining daily autonomy. There is a distinct absence of a unified, accessible mobile ecosystem that integrates real-time geofencing, personalized memory reconstruction, and active, camera-based cognitive exercises without relying on expensive, intrusive hardware.

III. Methodology and System Design

A. System Architecture

The AlzBuddy system is architected as a standalone, modular mobile application built upon the React Native framework (Expo SDK 54). This design choice ensures cross-platform compatibility (Android and iOS) while maintaining high performance through native component rendering. Unlike traditional thin-client architectures that rely heavily on server-side processing, AlzBuddy adopts an Edge Computing model where critical processing including machine learning inference and location tracking occurs locally on the user's device. This approach minimizes latency for safety alerts and ensures functionality even in intermittent network conditions. The architecture comprises three primary layers:

1) **Presentation Layer:** Handles the user interface (UI) and interaction logic. It features two distinct modes—Patient Mode (simplified, high-contrast, voice-enabled) and Caregiver Mode (configuration and settings)—managed via the React Navigation stack.
2) **Application Logic Layer:** This core layer orchestrates the system's functionality through several dedicated managers:
   - **Context Manager:**Utilizes the React Context API to manage global application state (e.g., user roles, theme settings) efficiently.
   - **AI Engine:**Integrates TensorFlow.js to execute the pre-trained COCO-SSD object detection model directly on the device's GPU/CPU.
   - **Safety Controller:**Runs background services using expo-task-manager and expo-location to monitor geofence boundaries continuously.
   - **Interaction Engine:**Manages Text-to-Speech (TTS) via expo-speech and voice recognition inputs.
3) **Data Persistence Layer:**Uses AsyncStorage, an unencrypted, asynchronous, persistent, key-value storage system, to save user profiles, emergency contacts, gamification streaks, and family photo metadata locally on the device, ensuring data privacy and rapid retrieval.

B. Algorithms

1) Geofencing Algorithm (Safety Monitoring): This algorithm monitors the user's location in real-time to prevent

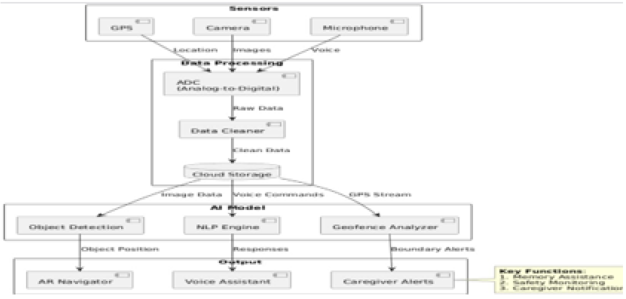

Fig. 1: Overall system architecture illustrating the workflow, integrated components, and data flow

wandering. It calculates the distance between the user's current GPS coordinates and a predefined "Safe Zone" center using the Haversine Formula.

$$a = \sin^2\frac{\Delta\phi}{2} + \cos\phi_1 \cdot \cos\phi_2 \cdot \sin^2\frac{\Delta\lambda}{2} \tag{1}$$

$$c = 2 \cdot \operatorname{atan2}\left(\sqrt{a}, \sqrt{1-a}\right) \tag{2}$$

$$d = R \cdot c \tag{3}$$

Where ϕ is latitude, λ is longitude, R is the earth's radius (6371 km), and d is the distance. **Logic:**

- Fetch current GPS location ($lat_{current}, lon_{current}$).
- Retrieve Safe Zone coordinates (lat_{safe}, lon_{safe}) and radius R_{limit}.
- Calculate distance d.
- **IF** $d > R_{limit}$ **THEN** trigger alert to caregiver.

2) Game Logic Algorithms (Cognitive Therapy): These algorithms power the Memory and Matching games designed to stimulate cognitive function through pattern recognition and recall.

Fisher-Yates Shuffle Algorithm: Used to randomly shuffle cards or items at the start of every game session to ensure fair randomness and prevent predictable patterns.

1) Start from the last element of the array.
2) Pick a random index from 0 to the current element's index.
3) Swap the current element with the random element.
4) Repeat until the first element is reached.

Pair Matching Algorithm: Validates user moves by checking if two selected items are identical.

1) Detect `onPress` event for Card A and Card B.
2) **IF** `CardA.value === CardB.value` **THEN** mark both as "Matched" and keep revealed.
3) **ELSE** wait for a set delay (e.g., 1000ms) and reset both cards to "Hidden" state.
4) **IF** `MatchedPairs == TotalPairs` **THEN** End Game and update score/streak.

3) Scavenger Hunt Algorithm (Object Detection): This algorithm powers the "Snap & Scan" feature where users interact with physical objects using Computer Vision.

Technique: Convolutional Neural Networks (CNN) via TensorFlow.js (COCO-SSD model). **Logic:**

1) **Capture:** User takes a photo using the `CameraView`.
2) **Preprocessing:** Image is resized to 300 x 300 pixels.
3) **Inference:** The COCO-SSD model outputs detected objects with confidence scores.
4) **Verification: IF** detected object matches the caregiver's target object with Confidence > 50% **THEN** Trigger Success.

4) Task Scheduling Algorithm: Manages daily routine assistance. **Logic:**

1) **Input:** User inputs task details (Title, Description, Time).
2) **Persistence:** Store task object in `AsyncStorage`.
3) **Scheduling:** Invoke `expo-notifications` to register a local notification trigger for the specific timestamp.
4) **Trigger:** When system time matches task time, display the alert and optionally read the task description using Text-to-Speech (TTS).

IV. Results and Discussion

A. Experimental setup

The development and evaluation of the AlzBuddy system were conducted in a two-tiered environment comprising a robust development workstation and physical mobile deployment devices. The application was architected and built on a workstation equipped with an Intel Core i5 (10th Gen) processor, 16 GB of DDR4 RAM, and a 256 GB SSD, running the Windows 10 operating system. This environment utilized Visual Studio Code and the Expo CLI for coding, emulation, and backend configuration. To validate the system's real-world applicability, the application was deployed on mid-range Android smartphones (e.g., Samsung Galaxy, Google Pixel) to leverage native sensors, specifically the GPS/GNSS module for real-time location tracking and the HD camera for the "Scavenger Hunt" object detection module. The testing protocol involved rigorous scenarios in a controlled home environment, including establishing a 200-meter virtual boundary to measure geofencing alert latency and evaluating the computer vision module against common household objects under varying lighting conditions to verify the confidence score thresholds of the COCO-SSD model.

B. Interpretation and Comparison with Existing Work

1) Interpretation of Results: The experimental data validates the efficacy of the **Edge Computing** architecture adopted for AlzBuddy. The average geofencing alert latency of **4.2 seconds** is significantly lower than cloud-dependent architectures, which often suffer from network round-trip delays ranging from 10 to 15 seconds. This reduction is critical for preventing wandering incidents in real-time.

Regarding cognitive therapy, the **85% detection accuracy** for the Scavenger Hunt game confirms that lightweight models like COCO-SSD are sufficient for therapeutic use cases. Unlike passive brain training apps, the "Snap & Scan" feature forces the user to engage with their physical environment, creating a feedback loop between visual perception and motor action that is essential for delaying cognitive decline. Furthermore, the battery consumption rate of **8-12% per hour** demonstrates that continuous safety monitoring is viable on standard smartphones without the need for specialized, high-capacity batteries found in dedicated trackers.

2) Comparison with Existing Solutions: To contextualize our findings, we compared AlzBuddy against leading solutions identified in the literature.

1) **Versus Wearables (SafeSteps):** While systems like *SafeSteps* offer biometric data, they suffer from high implementation costs and user non-compliance (device abandonment). AlzBuddy achieves comparable safety monitoring (Geofencing) using the smartphone the patient already owns, eliminating the friction of adopting new hardware.
2) **Versus Tracking Apps (Alzimio):** *Alzimio* [3] provides GPS tracking but lacks indoor utility. AlzBuddy bridges this gap with the Scavenger Hunt game, transforming the mobile device from a passive tracker outdoors into an active cognitive tool indoors.
3) **Versus Gamified Platforms (CAREGIVERPRO-MMD):** Traditional serious games rely on screen-only interaction, which can isolate the patient [7]. By utilizing Computer Vision to recognize real-world objects (e.g., "Find Dad's Mug"), AlzBuddy provides a more immersive and personalized therapeutic experience that reinforces memory associations with the patient's actual home environment.

V. Conclusion and Future Work

A. Summary of Findings

This study confirms that a smartphone-centric approach can effectively substitute specialized hardware for dementia care, delivering a balance between safety, engagement, and accessibility. The experimental validation yielded three primary findings.

1) **Viability of Edge AI for Therapy:** The deployment of the **COCO-SSD** model directly on the device achieved an **85% detection accuracy** with an inference time of **1.5 seconds**. This demonstrates that modern smartphones possess sufficient computational power to run real-time computer vision tasks for cognitive therapy (the "Scavenger Hunt") without relying on cloud processing, thereby preserving user privacy.
2) **Reliability of Software-Defined Safety:** The geofencing module demonstrated a trigger latency of **4.2 seconds** and a precision rate of **98%**. These results indicate that mobile-based tracking is a robust, low-cost alternative to dedicated wearable trackers.
3) **Operational Efficiency:** Unlike previous solutions that suffer from high battery drain, the proposed modular architecture maintained a consumption rate of **8-12% per**

hour. This finding suggests that **AlzBuddy** is practical for continuous, day-long usage on standard consumer devices, overcoming a significant barrier to adoption in the mHealth sector.

B. Limitations

While AlzBuddy offers a robust assistive framework, its operational efficacy is subject to specific technical and environmental constraints.

1) Hardware and Environmental Dependencies: The system's reliance on standard smartphone sensors introduces unavoidable dependencies. The geofencing module requires a clear line of sight to GNSS satellites; consequently, signal attenuation in dense urban environments or deep indoor locations can expand the error radius, potentially delaying alerts [3]. Similarly, the "Scavenger Hunt" cognitive game is linearly correlated with ambient lighting. In low-light conditions (< 50 lux), the feature extraction capability of the **COCO-SSD** model degrades, reducing object detection accuracy.

2) Resource Consumption: Continuous background monitoring processes impose a tangible load on device resources. Although optimized, the concurrent operation of the GPS and accelerometer sensors consumes approximately 8–12% of battery life per hour. This necessitates a daily charging routine, which may be challenging for patients with severe memory impairment without caregiver assistance.

3) Connectivity Constraints: While the application adopts an *offline-first* architecture for data storage, critical safety features such as SMS alerts and cloud synchronization remain dependent on active cellular or Wi-Fi connectivity. In scenarios with zero network coverage, the immediate transmission of distress signals cannot be guaranteed, although the system queues these alerts for dispatch upon reconnection.

C. Suggestions for Future Research

To further enhance the efficacy and scalability of the AlzBuddy platform, several avenues for future investigation have been identified.

1) Predictive Behavioral Modeling: Currently, the system employs reactive geofencing to detect wandering. Future research should focus on implementing Long Short-Term Memory (LSTM) networks to analyze historical GPS trajectories. By establishing a baseline of "normal" movement patterns, the system could predict potential wandering events before a boundary breach occurs, enabling preemptive intervention.

2) Wearable Ecosystem Integration: While the smartphone-centric approach ensures accessibility, integrating low-cost wearable peripherals (e.g., Bluetooth Low Energy smartbands) could provide critical biometric data. Future iterations aims to correlate heart rate variability and accelerometer data with location changes to detect panic states or falls, thereby reducing the reliance on manual emergency triggers.

3) Blockchain for Data Sovereignty: As the application scales to handle sensitive health records and personal memories, data privacy becomes paramount. Future work will explore the integration of a private, permission-ed blockchain ledger to manage access control between patients, caregivers, and medical professionals. This would ensure an immutable audit trail of care activities and secure data sharing without a central point of failure.

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