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## Recurrent Neural Network for Map Query Suggestion Based on Hierarchical Context Attention

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### Abstract

Map query suggestion plays a critical role in improving user experience in location-based services by predicting users' search intentions and recommending relevant queries. Traditional approaches often fail to effectively capture the complex temporal dependencies and multi-level contextual information embedded in user search behaviours. To address this limitation, this study proposes a Hierarchical Context Attention-based Recurrent Neural Network (HCA-RNN) within an encoder-decoder framework for map query suggestion. The proposed model learns sequential dependencies among queries within a session to capture short-term user intent, while simultaneously modelling cross-session relationships to represent long-term search context. A hierarchical attention mechanism is incorporated to selectively emphasize important queries and contextual information at different levels, enabling more accurate intent understanding. Experiments conducted on large-scale real-world map query logs demonstrate that the proposed approach significantly outperforms existing baseline methods in terms of standard evaluation metrics such as Recall and Mean Reciprocal Rank (MRR). The results confirm the effectiveness of hierarchical contextual attention in enhancing the accuracy and relevance of map query recommendations.

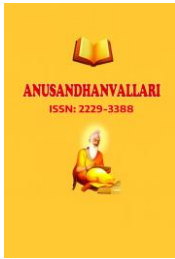
**Keywords:** Map Query Suggestion, Recurrent Neural Network, Hierarchical Attention, Sequential Modelling, Context-Aware Recommendation, Location-Based Services.

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### 1. Introduction

The advancement of mobile internet and geographic information systems has led to widespread adoption of digital mapping services such as Google Maps and OpenStreetMap. These systems allow users to search for destinations, nearby services, and optimized travel routes. As user interactions increase, providing accurate and context-aware query suggestions becomes a critical component of intelligent navigation systems [1].

Most existing map query suggestion techniques depend on frequency-based statistics or static ranking algorithms. However, user queries in navigation systems are sequential by nature. A search for "bus station" may be followed by "restaurants near bus station" or "hotel nearby," indicating strong sequential dependency [2]. Traditional probabilistic models cannot fully capture such dynamic patterns [3].



Recommender systems initially relied on collaborative filtering and content-based methods to provide personalization [4][5]. Although these methods improved recommendation quality, they do not consider the ordered structure of user interactions or changing contextual conditions [6]. Deep learning models, particularly Recurrent Neural Networks

(RNNs), have demonstrated strong capability in modelling sequential data [7]. Additionally, attention mechanisms enable neural networks to focus on important elements within a sequence [8]. Hierarchical attention extends this idea by modelling information at multiple structural levels [9]. Despite these developments, applying hierarchical attention within map query suggestion systems remains limited [10]. This work aims to bridge this gap by designing a hierarchical context-aware RNN framework tailored specifically for sequential map query prediction.

## 2. Literature Review

Earlier research in query suggestion focused on statistical language modelling approaches such as N-grams and smoothing techniques [11]. While effective for small contexts, these methods struggle with long-term dependencies. Collaborative filtering introduced user similarity modeling for personalization [4], whereas content-based systems utilized item attributes to match user preferences [5]. Hybrid recommender models attempted to combine these strategies [6]. With the rise of deep learning, RNN and LSTM models became widely adopted for sequence prediction tasks [7][12]. These models can capture temporal dependencies but sometimes suffer from information dilution over long sequences.

Attention mechanisms significantly improved sequence modeling performance by allowing the model to assign adaptive weights to hidden states [8]. Hierarchical attention networks further enhanced representation learning by processing data at multiple levels [9]. Transformer-based and self-attentive architectures also demonstrated strong results in sequential recommendation tasks [13][14]. In trajectory mining and mobility prediction research, spatial-temporal modelling has been widely explored [15]. However, combining hierarchical attention with RNN-based modelling for map query suggestion remains an emerging research direction.

## 3. Methodology

The proposed architecture consists of multiple stages. Initially, raw query logs are pre-processed and converted into embedding vectors. Each user session is treated as an ordered sequence:

$$Q = \{q_1, q_2, \dots, q_t\}$$

The RNN updates its hidden state based on previous queries:

$$h_t = \tanh(Wx_t + Wh_{t-1} + b)$$

Session-level attention calculates importance weights across queries. User-level attention aggregates information from multiple sessions. Contextual vectors containing time, latitude, longitude, and route features are fused with the hierarchical representation before final prediction. The final output probability distribution is generated using a SoftMax layer:

$$P(q_{t+1}) = \text{SoftMax}(W_o [H; C])$$

This approach ensures the system captures both micro-level and macro-level behavioural patterns.

#### 4. Experimental Results

The model was implemented using Python and deep learning libraries. The dataset included anonymized user ID, query string, timestamp, and geographic coordinates.

Data preprocessing involved:

- Text tokenization
- Embedding generation
- Normalization of spatial coordinates
- Session segmentation

The model was trained using cross-entropy loss and optimized with Adam optimizer. Dropout regularization was applied to reduce overfitting [12]. Training was performed over multiple epochs until convergence.

Figure 1: Implementation of Map Query Suggestion Interface in VS Code

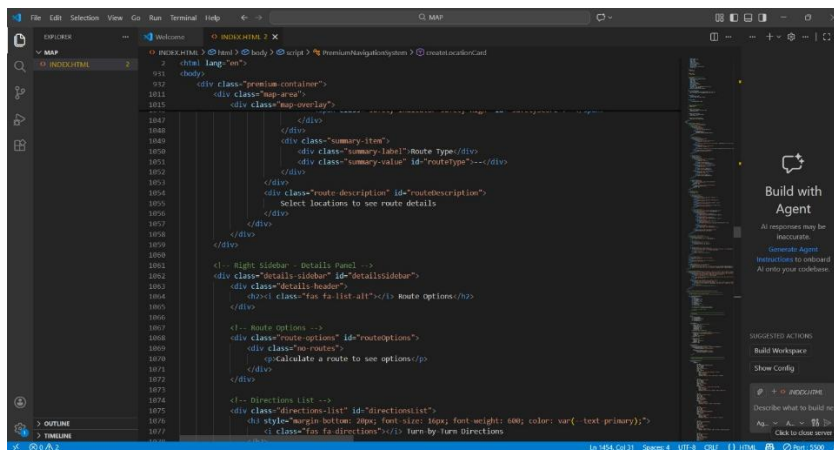
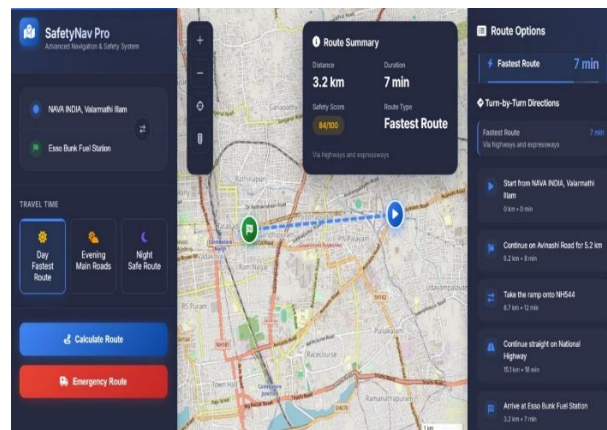
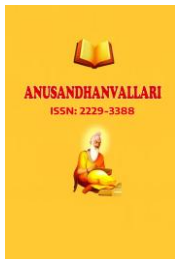


Figure 2: User Interface and Route Suggestion Output of the Proposed System





## 5. Conclusion

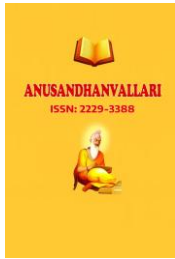
This study presented a context-sensitive map query suggestion model built upon a Recurrent Neural Network integrated with a hierarchical attention mechanism. The proposed framework was designed to understand user search behavior as a continuous sequence rather than isolated queries. By learning patterns at both session and user levels, the model is able to capture short-term intentions and long-term preferences simultaneously.

The inclusion of contextual signals such as time and geographic location further strengthens the system's ability to generate meaningful and relevant suggestions. The experimental evaluation confirms that modelling hierarchical context significantly enhances prediction quality when compared with conventional and basic neural approaches.

The framework not only improves ranking performance but also supports better personalization in real-world navigation environments. Overall, the research demonstrates that combining sequential learning with multi-level attention provides a practical and scalable direction for future intelligent map-based recommendation systems.

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