*I. J. Education and Management Engineering,* **2025, 2, 11-18**
Published Online on April 8, 2025 by MECS Press (http://www.mecs-press.org/)
DOI: 10.5815/ijeme.2025.02.02

# Query Auto-Completion Using Relational Graph Convolutional Network in Heterogeneous Graphs

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Received: 22 April, 2024; Revised: 24 June, 2024; Accepted: 22 July, 2024; Published: 08 April, 2025

**Abstract:** Search engine acts as an interface between users and computers. Online search is a very quick and impactful evolution of human experience. It is becoming a key technology that people rely on every day to get information about almost everything. Searching is typically performed with a common purpose underlying the query. If the user does not know the knowledge of the keywords to be searched, spends more time to frame the query. The search may not contain the user's intended answers. Understanding the meaning of the query given by the user is the important role of the search engine. The query auto-completion feature is important for search engines. The query auto-completion process occurs uninterruptedly, dynamically listing terms with each click. It provides recommendations that facilitate query formulation and improve the relevancy of the search. Graphs and additional data structures are used frequently in computer science and related fields. The applications of graph machine learning include data recovery, friendship recommendation, and social networking. Heterogeneous graphs (HGs) consist of different kinds of nodes and links, and are useful for defining a wide range of complicated real-world systems a robust graph neural architecture for encoding a knowledge graph is the Relational Graph Convolutional Network (R-GCN).The proposed model uses the supervised Relational Graph Convolutional Network(R-GCN), Long Short-Term Memory (LSTM) for completion of the query. The model predicts the object given the subject and predicate and the accuracy is 92.4%.

**Index Terms:** Heterogeneous graphs (HGs), Query Auto-completion (QAC), R-GCN Relational Graph Convolutional Network, LSTM-Long Short-Term Memory

## 1. Introduction

Heterogeneous graphs are made up of different types of nodes and different relationship exist between the nodes .These graphs are found in a wide range of real-world contexts, including recommendations systems social networks and bibliographic networks. Heterogeneous graph is defined as G=(V,E,R,T), nodes with nodes type $V_i$ €V, edges with relation type ( $V_i$ r $V_j$ ) € E, Node type T($V_i$) , relation type r €R.

The current search engine provides a vast volume of results for a given inquiry but has many concerns, such as poor accuracy. By taking into account both the user's purpose and the significance of phrases in various contexts, semantic exploration becomes more accurate [1]. The most significant feature of the current search engine is query auto-completion (QAC) [2]. Reducing the user's workload and assisting them in overcoming obstacles like composing long texts, making typos, and finding suitable query phrases are the main fundamental objectives of a QAC system [3].

As seen in Figure 1, the process of query completion starts with the letters that the user enters in the search field (Figure 1.a) and changes as they type (Figure 1.b).

 

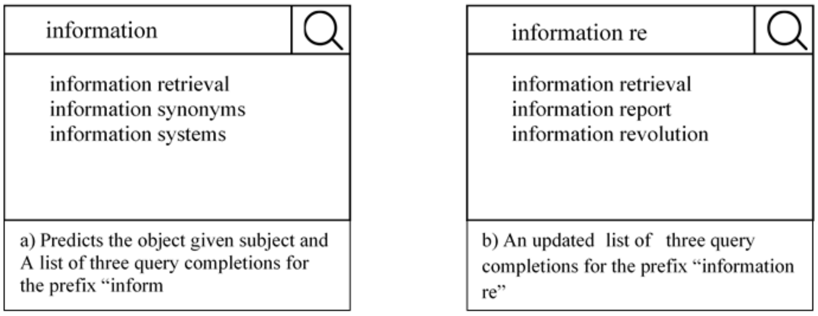


Fig. 1. Example of query auto Completion

Present data is searched using syntactic-based search engines, primarily from HTML material that yields irrelevant results. Query auto completion is the first step that every search engine does. It's a feature that allows for interaction. To generate the query quickly is by proposing a collection of terms for each keystroke in real-time depending on the user's previous search popular term [27]. A semantic-based search engine helps to understand the meaning of the query and returns results that are more relevant. Hakia, Swoogle, and DuckDuckGo are examples of semantic Web search engines that retain semantic data about web pages and may answer difficult queries by considering the context in which the resource is discussed. Semantic Web and search engine technologies are combined to create semantic search, which leverages semantics to enhance current search engine results and set the framework for future search technologies. Ontology usage increases the precision of web searches. It offers initial understanding of a field. Uncertainty in information representation and a lack of semantics are problems with the present QAC procedure.

The Semantic Web is an enhancement of the existing World Wide Web (WWW). It makes it possible to conduct a web search depending on the meaning. World Wide Consortium (W3C) standards are used in the Semantic Web. The Semantic web is an intelligent mesh that permits people to share significant facts and representations over the internet. Ontology facilitates, the associations between individuals and classes of things that constitute a knowledge base. Artificial Intelligence applications are built using the knowledge base [4].

A high level of conceptual comprehension of the knowledge and an understanding of the connections between entities are both possible with ontology. Query formulation, ranking, indexing, and expansion is done using Ontology [5]. Domain metadata with associated semantics taken from the relational database schema could be represented using domain ontology [6]. Using ontology in data recovery has yielded more accurate outcomes.

Numerous issues, including interoperability, business model consistency, and tourism-related knowledge architecture, are resolved by ontology. Tourism business models, procedures, and knowledge architectures are all managed partially by ontologies. A paradigm of information representation called ontology can be used to build knowledge bases that provide solutions for specific situation [28].

A case study on the ontology of tourism is presented, showing where the nation's tourist attractions are located. For the tourist ontology, concepts, relations, examples, and axioms are the essential elements. In the tourism industry, an idea refers to a class or group of things. Each class defined by the ontology describes a certain feature. OWL provides predefined classes, such as owl:Class and owl:Thing. The type of the class definition is owl:Class. Figure 2 shows the ontology for tourism domain.

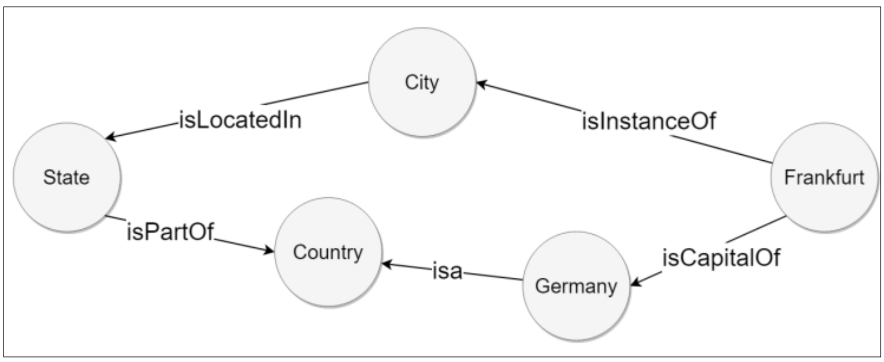


Fig. 2. Ontology for tourism domain

The Semantic Web's most often used terminologies are Resource Description Framework (RDF) and SPARQL. RDF is a standard method of presenting data on the SW. A triple store is where RDF data that makes up triples are stored. Subject, predicate, and object are the three triples. The term "predicate" refers to the connection between the subject and the object. The figure 3 depicts the RDF statement.

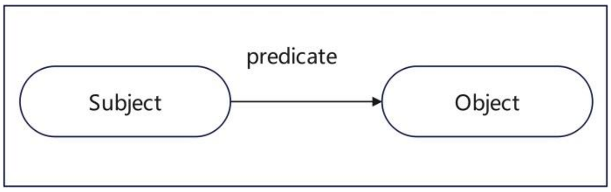


Fig. 3. Representation of RDF Statement

The graph's nodes represent resources, the attributes represent node labels, and the graph's edges represent assertions between two resources. SPARQL is the language used to query RDF data [7].

The Knowledge Graph displays the evidence, entities, interactions, and semantic details. Entities are things that are related to both real things and intellectual ideas. The term "relationship" refers to the method of determining the relationship between two or more terms. The attributes of objects having a determined meaning are included in the semantic definition. In a knowledge graph, entities are represented as nodes, and relationships between nodes are represented as edges. A self-sufficient Semantic Web is a knowledge graph that spreads across the whole network [8].

Knowledge Graphs (KGs) is a powerful graph-based knowledge representation that has led to an evolution in various Artificial Intelligence assignments. The objective of the link prediction task is to learn the embedded representation of objects and interactions in knowledge graphs. Knowledge graph embedding techniques explain entities and related embeddings in a low-dimensional space, which are then applied to machine learning tasks such as entity matching and link prediction.

Nodes in a Knowledge Graph have various sorts of relationships therefore the relevance of neighbors is determined by their own characteristics and also by the features of the links [11]. Knowledge graph creation is depicted in Figure 4. A reasoner is used by the KG to gather special information.

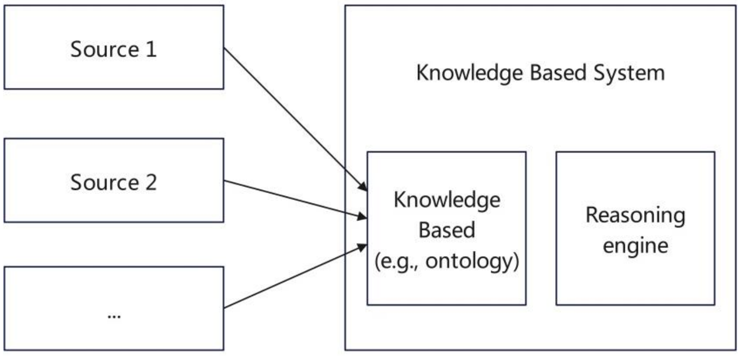


Fig. 4. Architecture of Knowledge Graph

The graph convolutional neural network (GCN) architecture is a graph neural network that uses convolution layers to build graph embeddings. Graph neural network are employed to gain insight into the embedding of a graph and is used to execute various tasks.

Knowledge graph convolutional networks (R-GCN) take edge heterogeneity into account and use a message-passing framework to build a new representation of a head node by applying some relation-specific transformation on neighbor representations before aggregating at the head node [11].

This paper, a concise analysis of associated work is presented in section 2, the projected approach design is projected in section 3 and, in section 4 discussions and results are accessible and section 5 conclusion.

## 2. Literature Review

The literature survey reveals that Graph Convolution Networks uses various categories of data to study the characteristics of entities and relations. In contrast Relational Graph Convolution Networks (RGCN) deals with multi-relational data.

A novel embedding approach called Trans4E moves the entities of a graph via relations in the Quaternion vector space $H^d$. $H^d$ is appropriate for KGs with N to M relations and N >>M. The model performs the set of steps. The head entity vector $h \varepsilon H^d$ is rotated by $r_\theta$ degrees in quaternion space. The relation embedding vector r deduces the rotated head $h_\theta$ to get $h_r = h_\theta + r$. The embedding vector of the head congregates the embedding vector of the tail for a positive sample. The model is effective with the scheme known as a shallow classification that uses low embedding dimensions [9].

It is recommended to use recalibration convolutional networks in a multi-layer link prediction method. The objective is to learn entities and relations interaction embeddings that incorporate their cross-semantic effect, which entails unique triplets, in order to address the issue of semantic polysemy that occurs in knowledge graph. The interaction embedding added to the recalibration convolutional networks is to enable the networks to automatically learn and selectively boost informative features. To predict the chances of a proper triplet, features are vectorized, transferred into the embedding dimension, and computed via an inner product with the candidate entity embedding [10].

Researchers suggest an email search technique using on-device QAC. The QAC system is customised to each user's specific email corpus since it is fully integrated with the on-device email retrieval and grading systems. QAC candidates are generated from emails that rank highly. They can be retrieved for more than just consecutive n-grams. Features of the ranked candidates are effective and simple to use. Additionally, researchers suggest a brand-new offline assessment technique based on private corpora for gauging the quality of QAC on-device. This strategy performs better than robust baseline algorithms, according to experiments [28].

Graph Convolution Networks are able to understand the properties of entities and relations. The methods assign equal weight to the neighbours while aggregating the data. It ignores the significance of different interactions with neighbouring models. By assigning weights to neighbouring nodes based on relational data, the graph attention model learns entity and relation embeddings. An entity's embeddings are updated by transferring its peers' properties through the use of attention. A better representation can be studied with the aid of the attention mechanism [11].

A type of neural network called R-GCN operates on graphs and processes the multi-relational data present in real-world knowledge repositories. R-GCNs can be applied to link prediction as an improved factorization model or as a stand-alone model entity classification. DistMult, an encoder model is used to increase the performance by accumulating evidence over numerous inference steps in the relational graph. An auto-encoder consists of:

1. An encoder: R-GCN generates latent element characteristics of entities.
2. Decoder: To predict labeled edges, a tensor factorization model uses the latent feature descriptions of entities[12].

The Knowledge graph is created for the tourist attractions by using tourism data. Creation of feature vectors of both visitors and attractions using the network representation learning technique Node2Vec.The correlation ratings between tourists and attractions are calculated using cosine similarity. The recommended list is generated by normalizing the correlation scores [14]. The main objective of the knowledge graph is to conceptually and semantically place the entities and relations of a KG in the low-dimensional space. To investigate how concepts and entities are semantically connected, the skip-gram model is used. When paired with concept information, entity embedding's perform better than textual information for entity classification. [15].

Sequential multi layered Recurrent neural Network is presented to forecast the triples in a KG. The model predicts the tail elements of the triples. A beam search strategy with a big window size is applied [16].Entity link for knowledge graph (ELPKG) is a novel method developed to increase the accuracy of link prediction. To recognize the relationship between things, an entity link prediction method is used. For understanding the relationship between things, a probabilistic soft logic-based reasoning approach is employed, which incorporates methods and semantic-based elements. Tuple similarity is measured using the Euclidean distance. The two tuples are comparable if their distance from one another is the shortest. The similarity is computed between the distances between the two tuples. Shorter the distance similarity value is high. The unknown relations in the Knowledge Graph are reported by this ELPKG. [17].

The prediction of relationships is the focus of a multi-label deep neural network model. The goal of this model is to predict how the entities in a knowledge network will interact. For the completion of knowledge graphs and the creation of extensive ontologies, link prediction between items is essential. If the relationship is correctly predicted, an ontology can include it [18].

Resource Description Framework, a semantic web language, is used to create knowledge graphs. Real-valued tensors are used for embedding knowledge graphs. The knowledge graph's relationships are recovered using these tensor-based embedding's. The tensor decomposition approach works effectively when an entity's average degree in a graph is greater. This leads to an increase in the accuracy of forecasting new facts across the knowledge network [19].

The authors suggest a novel method that integrates bidirectional long short-term memory with convolutional neural networks. The training information is made up of a combination of precise and despoiled triples. A path ranking method is utilized to get the connected pathways that are significant to the relation r for each training instance. To know the relationship between the source object and its target random walks are used. A vector representation is used to grasp the semantic co-relationship between two elements and the path between them. The pathway between the entities is taken into account during the attention procedure. In an embedding area, this approach generates multistep reasoning over path representation. The path encoder is responsible for extracting the features from the edges in massive graphs [20].

The aggregation method extracts added entity and relational data, as defined by a Relational Aggregation Graph Convolution Network (RA-GCN). The RA-GCN model improves on the Graph Convolutional model in terms of extracting knowledge graph topological relationship properties. [21].

Heterogeneous information networks (HINs) are logical networks that include entities with varying relationships and are used to model real-world systems with complex patterns and rich attributes. GCNs can take into consideration both network structure elements and the intrinsic properties of vertices .Rather than generating features manually, GCNs can automatically study informative characteristics from raw graph data, which saves time and money. GCNs are divided into two types: spectral-based GCNs and spatial-based GCNs. Pattern recognition challenges such as graph similarity difficulties and graph similarity identification are solved using spectral GCNs. The key disadvantage of spectral GCNs is that individual GCN layer is involved in repeated matrix multiplication and has a high level of complexity in the event of big graphs, as well as the difficulty in determining the depth of GCNs, which directly impacts accuracy. The spatial GCN does not need an adjacency matrix and can handle enormous graphs. Spatial GCN selects nearby neighbors for each vertex, vectorizes the sub-graph by assigning an order to the vertices, and then feeds the vector into one-dimensional convolution layers to learn embeddings. By finding surrounding vertices that are structurally irrelevant, a community discovery based technique is proposed. The embeddings of the vertices are learned using a deep Convolutional neural network. By matching vertices from the new kernel layer, link prediction can be performed [22].

The literature review infers that the GCN layers are involved have a high level of complexity in case of heterogeneous graphs. The graph convolutional layer is improved by aggregating the relational and entity information. RDF, a semantic web language is used in creating a knowledge graph.

## 3. Proposed Architecture

The fig.5 depicts the flow diagram. Protégé is used to create ontology for tourism domain. Classes, property values, relationships between classes, and limitations on slots, properties, and individuals are all included. The query language SPARQL is used to generate triples (s,p,o). Graph-operating neural networks, or R-GCNs, are designed to handle highly multi-relational data environments. When the subject and predicate are known, the object is predicted using the LSTM model.

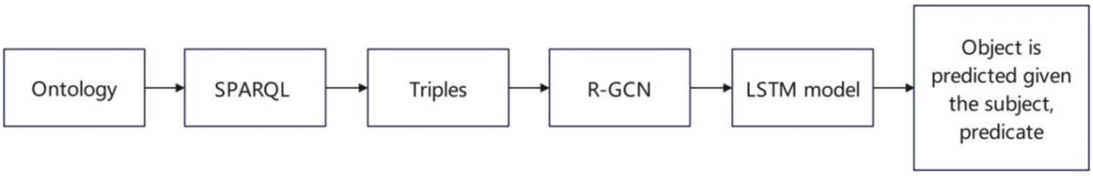


Fig. 5. Proposed Diagram

### *3.1 Recurrent Neural Network*

Recurrent neural networks may retain previous inputs and utilize them to generate the desired output. Artificial neural networks (ANNs) with feedback connections and recurrent neural networks (RNNs), are good at modeling sequence information for sequence prediction and recognition. RNNs are composed of high-dimensional states with non-linear dynamics. The RNN model receives the input x, and in the state h, the inputs are multiplied by a weight matrix to determine the neural network model's current state. At the input x, a neural network component h activates and produces the value y. Information can move from one network step to the next. The figure 6 shows the design of RNN, where x is the input word, h represent the hidden layers and $W_1$ is the weights allocated and y is the output at any given time.

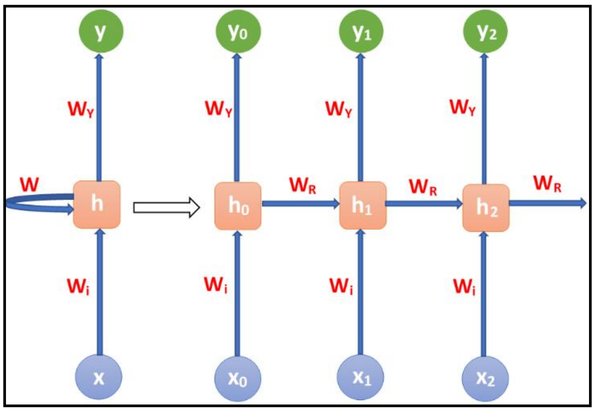


Fig. 6. Architecture of recurrent neural network

### *3.2 Long Short-Term Memory Model*

Long term dependencies are learnt by a superior form of RNN that is long short -term memory model. The fig 7 depicts the LSTM cell. The cell state is the essential component. It acts like a conveyor belt; the horizontal line represents this. The gates regulate what data can be added and removed from the cell state. The three gates are input, forget and output. The cell state is governed by the forget gate. The sigmoid layer determines whether the answer is 0 or

1.1 denotes holding, and 0 denotes elimination. The input gate updates the cell state.The information stored by the tanh output is determined by the sigmoid output. Monitoring the hidden states and storing the previous state is carried out by the output gate. Predictions are made using the hidden state [24].

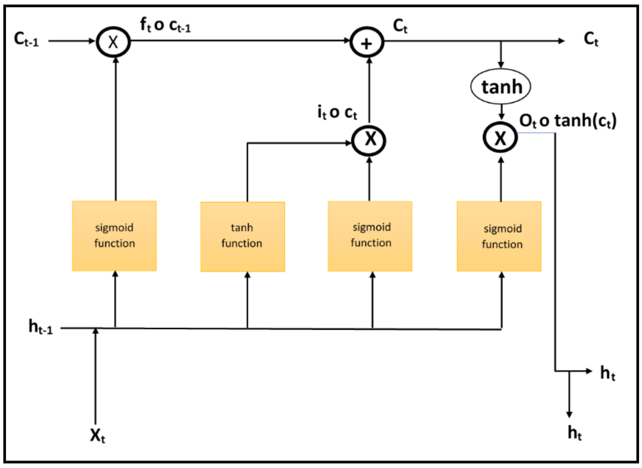


Fig. 7. LSTM cell

## 4. Implementation

### *4.1 Dataset*

The Protégé takes the input as URL and Ontology is created. The structure of the ontology is as follows

<!-- http://www.semanticweb.org/vd/ontologies/2024/11/vd#isCapital -->
<owl:ObjectProperty rdf:about="&vd;isCapial">
<rdfs:subPropertyOf rdf:resource="&vd;isSituated"/>
</owl:ObjectProperty>

The data is queried by using SPARQL and the data is presented as subject predicate and object. The dataset is partitioned as 80% and 20%, training and testing dataset respectively. The dataset layout is as given below

Table 1. Dataset Format

| Subject | Predicate | Object |
|---|---|---|
| Goa | isCapital | Panjim |
| Goa | Isa | state |
| Goa | isSituated | India |

### *4.2 Evaluation Metrics*

The Mean Reciprocal Rank (MRR) is the evaluation statistic that is employed. For the same set of queries Q, the mean of the reciprocal rank of the outcomes is MRR.

$$MRR = \frac{1}{|Q|}\sum_{i=1}^{|Q|}\frac{1}{ranki} \qquad (1)$$

$Rank_i$ tells you about the rank position of the significant query, given the ith query[25].

## 5. Result and Discussion

Queries in the tourist domain are shown as nodes and edges in a graph. The representations of data is in the form of subject, predicate, and object. The Knowledge graph is encoded using a Relational-Graph Convolutional Network (R-GCN). With respect to the subject and predicate, the LSTM model predicts the object. The accuracy of the model is 92.4% in comparison of the model [27] whose accuracy is 89.4%. Node2vec uses an algorithm to identify the features of nodes inside a network. It employs p and q, two parameters that skew the random walk. Word2vec, a word embedding algorithm, generates node embeddings. By examining the connections between the entities, embeddings can be learned [27]. MRR score for this model is 86.2.

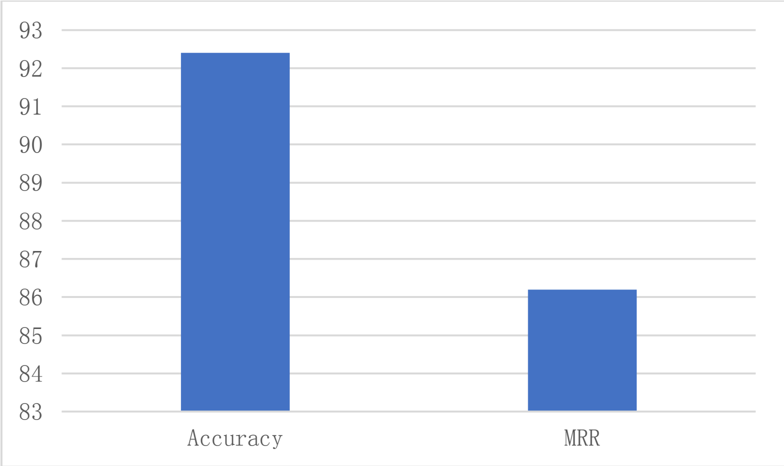


Fig. 8. Accuracy and MRR

## 6. Conclusion

Extracting relevant information from search outcome is a major difficulty since it does not happen instantly.To overcome the retrieval is performed semantically. The proposed model Long Short-Term Memory (LSTM-RGCN) is to predict the query terms. LSTM is a type of Recurrent Neural Network that excels in capturing long term dependencies. The tourist domain ontology is created. Data is constituted as subject, predicate, and object. Nodes represent entities, and edges represent relation. R-GCN is used to compute node embedding's in a Knowledge graph. The accuracy of this model is 92.4%. More the accuracy more relevant terms are predicted for query completion. Performance of this proposed model is greater by 3% compared to the model that uses Node2vec.

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**How to cite this paper:** Vidya Dandagi, Nandini Sidnal, Jayashree Kulkarni, "Query Auto-Completion Using Relational Graph Convolutional Network in Heterogeneous Graphs", International Journal of Education and Management Engineering (IJEME), Vol.15, No.2, pp. 11-18, 2025. DOI:10.5815/ijeme.2025.02.02