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Aspect Category Detection Using Bi-LSTM-Based Deep Learning for Sentiment Analysis for Hindi

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Abstract: In the field of sentiment analysis, the notion of aspect category identification lays emphasis on identifying the aspect categories in a specific review phrase. The purpose of this research is to propose a novel approach to the identification of aspect categories in reviews that are published in Hindi. The training and evaluation of a supervised model that is based on deep learning enable the extraction of aspect categories. Every experiment is carried out with a well-accepted Hindi dataset. One of the challenges that are involved in aspect category recognition is the classification of text that has several labels. The utilization of a deep neural network that is founded on BiLSTM leads to an enhancement of the category detection outcomes. The results came out with an F-score of 0.8345 and an accuracy of 93.91% when applied to the well-known Hindi dataset. The offered architecture, in conjunction with the results that were achieved, gives a great deal of significance because it serves as a fundamental resource for future research and activities related to the issue. In this study, a deep-learning architecture is proposed for the aim of detecting aspect categories in Hindi. The outcomes of this architecture are both new and state-of-the-art in their respective fields.

Keywords: Sentiment Analysis, Aspect Category Detection, Bidirectional Long Short-Term Memory, Multi-Label Text Classification, Deep Learning

Introduction

Internet users frequently express their opinions and sentiments about various topics, entities, or aspects through online posts such as reviews. Sentiments extracted from such posts can be precious. Opinion mining, or sentiment analysis, automatically detects and extracts sentiment or opinion from digital texts using natural language processing methods. As online reviews and opinions in Indian languages such as Hindi have increased significantly with the number of Indian Internet users, sentiment analysis in Indian languages is an urgently needed field of study. Conventional sentiment analysis (Chauhan *et al*., 2023) attempts to consolidate the sentiment into a single value such as positive, negative, or neutral. However, a single review may contain different opinions about different entities or aspects of an entity. Aspect-Based Sentiment Analysis (Trisna and Jie, 2022) (ABSA) addresses this fine granularity. In ABSA, the finer-level aspect terms are extracted and categorized. Aspect category detection allocates a subset of predefined categories to a particular review. For example, consider the established list of restaurant aspect categories, price, ambiance, service, and general, and the following review.

"*Highly Praise that as Great Value for Excellent Pizza and Service*"

The two phrases "pizza" and "service" belong to existing aspect categories "food" and "service". A review may have multiple terms for an aspect category. Also, aspect category detection helps achieve multi-label text classification.

Related Works

Aspect category detection is vital to extracting critical insight from the input text. It can help with content recommendation, information retrieval, etc. Xue *et al*. (2017) proposed a multi-tasking neural network that addresses aspect category detection and aspect term extraction for English. The model employed a BiLSTM layer. Experiments were demonstrated on the SemEval dataset. 0.7642 F-score reported for the SemEval dataset. Existing literature (Chebolu *et al*., 2023; Liao *et al*., 2021; Kumar *et al*., 2022; Kumar and Abirami, 2021; Haq *et al*., 2023) reports aspect category detection in Arabic (Almasri *et al*., 2023), Turkish (Ozyurt and Akcayol, 2021) and Vietnamese (Van Thin *et al*., 2022) languages.

Machine learning (Akhtar *et al*., 2018) and deep learning-based (Hetal, 2021) aspect category detection

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is reported for the Hindi language, too. These all experiments were performed on the Hindi Review Sentiments Dataset (Akhtar *et al*., 2018).

Akhtar *et al.* proposed binary relevance and label power set (Han *et al.*, 2023) approaches on freely available Hindi Review Sentiments Dataset (Akhtar *et al.*, 2018). They obtained 0.46, 0.56, 0.30, and 0.64 F-scores for aspect category detection tasks in Electronics, Mobile apps, Travel, and Movies domains, respectively. Hetal (2021) performed aspect category detection based on the Feed-forward Neural Network (FNN) approach. They performed experiments on the Hindi Review Sentiments Dataset (Akhtar *et al.*, 2018) and achieved 0.67, 0.69, 0.56, and 0.72 F-scores for Electronics, Mobile apps, Travels and Movies domains, respectively. FNN treats words as independent features and does not explicitly consider the order of words. Hence, FNN has limitations for text processing.

Hindi is a free-order language (Khurana *et al.*, 2023; Kumar *et al.*, 2023). A BiLSTM unit is capable of understanding order dependence. When sequential data is processed in the BiLSTM unit, it is processed simultaneously in both the forward and backward directions. The power of BiLSTM to capture context, which helps in the management of imbalanced classes, makes it simpler to comprehend the links that exist between instances. This is because context is necessary for the administration of imbalanced classes. It may result in a higher F-score thanks to the fact that it has the potential to improve both recall and precision. BiLSTM outperformed other reported work and models like GRU and traditional LSTM. Other models often need help with vanishing gradient problems, leading to poorer performance in long-range dependencies. Our approach incorporates attention mechanisms alongside BiLSTM to synergistically enhance performance. This combination allows the model to focus on the most relevant parts of the input sequence, significantly improving overall accuracy.

We have made the following primary contributions as a result of our work: (i) Aspect category detection is formulated as a multi-label problem, and (ii) Proposed a novel deep learning-based method for aspect category detection. Experiment results of our supervised model on a well-accepted Hindi dataset (Akhtar *et al*., 2018) demonstrate that our method outperforms strong baseline reported work in the Hindi language significantly.

Materials and Methods

The deep BiLSTM model is presented for the purpose of aspect category recognition and is composed of two components: One dense layer, one Bidirectional Long Short-Term Memory unit, and one output layer. Both of these components are contained within the model. It is the responsibility of the multi-label assignment module to assign one or more aspect categories to each and every single Hindi sentence that is included in the dataset.

A pre-processing step is performed on each and every sentence that is included in the dataset. The Hindi dataset is comprised of three separate sets: The training set, the validation set, and the test set. On the training set, the model gets trained. The model uses the test set for accuracy analysis. A validation set is used to achieve the goal of fine-tuning the hyperparameters of the model. The employment of the sigmoid function in the final output layer is the primary method utilized to accomplish aspect category detection.

The BiLSTM layers make it possible for the model to take into consideration the intricate dependencies and contextual information contained within the input. It is possible to have a full understanding of the context thanks to the BiLSTM unit's ability to process sequences in both a forward and backward orientation. It is also useful for tasks like aspect category recognition, which require careful analysis of the context of words and the linkages between them inside sentences. This is especially effective for jobs like these. Figure 1 is an illustration of a statement that can be classified as belonging to the predicted aspect category of electronics. In the next section, we will discuss the preprocessing, the elements of the neural network, and the Hindi dataset, which is highly appreciated.

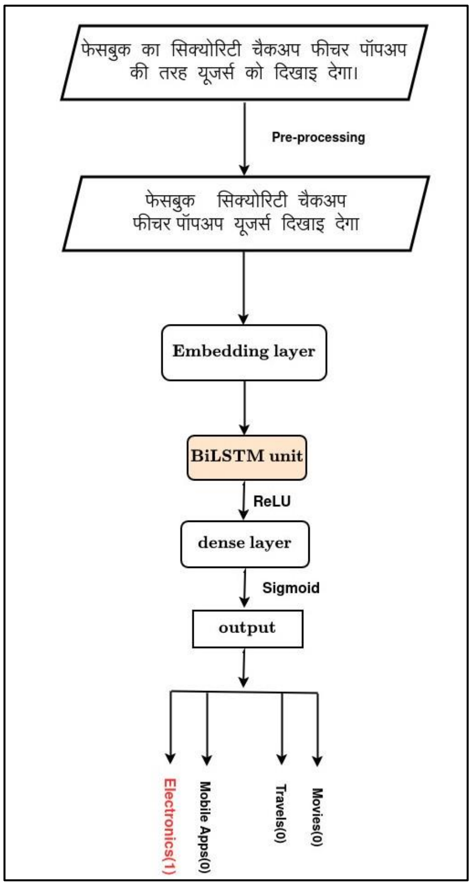

Fig. 1: Block diagram for proposed aspect category detection model

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Dataset Description

Hindi sentences are included in the Review Sentiments Dataset (Akhtar *et al*., 2018), which is a dataset that is available to the public without charge. These datasets were made accessible to the general public by the Indian Institute of Technology in Patna on their website. The configuration of the data collection is in XML (Extensible Markup Language). Two instances of the dataset with their structure are depicted in Table 1. The <sentences> node signifies the root node of the XML. It includes sentences of the review as its children, i.e. <sentence>. To exclusively categorize each <sentence>, an 'id' is associated with it <aspectCategories>. The <text> node comprises one review sentence, whereas <aspectCategories> can have zero or more <aspectCategory> nodes. It shows that the aspect category belongs to the multi-label paradigm. These nodes handle aspect category information. Each <aspectCategory> node holds 'category' and 'polarity' attributes. Attribute 'category' indicates the aspect term category represented by the present node, and 'polarity' indicates the sentiment of the 'term', which is pos (positive), neg (negative), or neu (neutral).

The Hindi review sentences in the IIT Patna dataset belong to the following categories: Design, ease of use, gui, hardware, music, performance, place, price, reachability, scenery, software, story, and misc. These categories are distributed unevenly in the dataset. Some categories are rare in the dataset. These aspect categories are grouped into 04 domains with the distribution represented in Table 2.

There are 5275 aspect categories with their polarity among these 4930 review sentences in the Hindi dataset.

4601 reviews have one aspect category. 313 reviews have two aspect categories. 16 reviews have three aspect categories.

Multi-Label Assignment

The following steps are performed using Python (Martelli *et al*., 2023) for multi-label assignment to the Hindi sentences:

1. Initialize an empty list to store Hindi sentence data and aspect category labels
2. Store each sentence in one row
3. Initialize with 0 to all aspect categories for each sentence
4. For each sentence:

    1) Identify and collect aspect categories
    2) Update the set of aspect categories with 1 for the present aspect categories

Table 1 presents two Hindi reviews from the IIT Patna dataset. Figure 2 shows the multi-label assignments for these two Hindi reviews.

Data Pre-Processing

Data pre-processing (Jurafsky and Martin, 2020) is vital for effective machine learning. It involves cleaning, standardizing, removing duplicates, and normalizing text data, which includes eliminating punctuation, tokenization, stemming for simpler words, and removing non-essential "stop words". An example of pre-processing on Hindi review for aspect category detection is illustrated below:

Hindi review (Before pre-processing)

फेसबुक का सिक्योरिटी चैकअप फीचर पॉपअप की तरह यूजर्स को दिखाइ देगा।

Hindi review (After pre-processing)

फेसबुक सिक्योरिटी चैकअप फीचर पॉपअप यूजर्स दिखाइ देगा

ID	Text	mobile_apps	electronics	movie	travel
app_2	फेसबुक का सिक्योरिटी चैकअप फीचर पॉपअप की तरह यूजर्स को दिखाइ देगा।	1	0	0	0
app_94	इसमे बहुत उच्च स्तर के ग्राफ़िक्स नही हैं लेकिन यह गेम बहुत आकर्षित करने वाला है।	1	0	0	0

Fig. 2: Multi-label assignment of reviews

Table 1: Hindi dataset labelled structure

Labelled structure
<sentences>
<sentence id="app_2" polarity="neu">
<text>फेसबुक का सिक्योरिटी चैकअप फीचर पॉपअप की तरह यूजर्स को दिखाइ देगा।</text>
<aspectCategories>
<aspectCategory category="gui" polarity="neu"/>
</aspectCategories>
</sentence>
<sentence id="app_94" polarity="con">
<text>इसमें बहुत उच्चस्तर के ग्राफ़िक्स नहीं हैं लेकिन यह गेम बहुत आकर्षित करने वाला है।</text>
<aspectCategories>
<aspectCategory category="gui" polarity="neg"/>
<aspectCategory category="misc" polarity="pos"/>
</aspectCategories>
</sentence>

</sentences>

Table 2: Reviews distribution in four major domains

Domain	Aspect Categories Domain	Distribution (%)
Electronics	Design (524), software (370), hardware (797), ease of use (122), price (228), misc (573)	68.51
Mobile apps	GUI (27), ease of use (29), price (11), misc (134)	3.81
Travels	Scenery (127), place (303), reachability (35), misc (105)	10.81
Movies	Story (35), performance (244), music (38), misc (573)	16.87

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Neural Network Elements

In order to develop the deep BiLSTM model that has been proposed, the following neural network elements are utilized.

Deep BiLSTM Neural Network

Two LSTMs combine to form the bidirectional LSTM (Vasumathi and Kamarasan, 2021; Chugh, 2019) sequence processing framework: One that takes the input ahead and the other that takes it backward. Both forward and backward LSTMs process the input sequence. We use BiLSTM for Hindi data because it captures context from past and future sequences, handling complex language structures and dependencies effectively. This bidirectional approach benefits Hindi's rich morphology and context-sensitive nature, improving performance in aspect category detection tasks. Additionally, BiLSTM can better manage the intricate grammatical rules and diverse word forms in Hindi, leading to a more accurate and nuanced understanding and generation of text. Its ability to process long-range dependencies makes it suitable for tasks involving Hindi's syntactic and semantic intricacies. LSTM is to save previously entered information or effectively maximize the amount of information available to the architecture. A systematic architecture of the LSTM unit is presented in Fig. 3. Under recurrent neural networks, The LSTM category provides cutting-edge results on several challenging prediction problems. Using gates to help with the correct flow of information is utilized to solve the short-term memory problem. The input gate, forget gate and output gate are the three gates that alter the cell state, which is the long-term memory in LSTMs. The following are the goals of these gates, which function as filters.

Input gate: Based on the prior hidden state and the current input data, this gate determines what data needs to be added to the LSTM cell state. Following is a description of the LSTM input gate principle:

$$i_T = \sigma(w_I[h_{T-1}, x_T] + B_I)$$
$$c'_T = hyperbolictan\,(w_I[h_{T-1}, x_T] + B_I)$$
$$c_T = f_T c_{T-1} + i_T c'_T$$

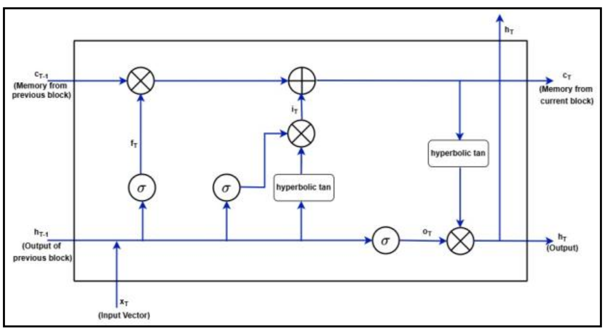

Fig. 3: LSTM unit architecture

c_T stands for memory information, B_I stands for input gate bias, w_I stands for weight matrices, and c'_T represents $hyperbolictan$ output. As in the above review, the input gate evaluates "फेसबुक" and decides how much of this new information to integrate.

Forget gate: This gate determines which portions of the cell state are valuable based on the input data that is currently being received and the previously concealed state. The output gate f_T working concept is described below:

$$f_T = \sigma(w_F[h_{T-1}, x_T] + B_F)$$

where, w_F denotes weight matrices, B_F represents offset and σ is the sigmoid function. If the previous context was about "फेसबुक", the forget gate will determine how much of this context to retain when processing "सिक्योरिटी".

Output gate: Based on the most recent cell state update, the previous hidden state, and the newest input data, the output gate determines the new hidden state. The output gate concept is illustrated here:

$$o_T = \sigma(w_o.[h_{T-1}, x_T] + B_o)$$
$$h_T = o_T\, hyperbolictan(c_T)$$

h_T is the hidden state.

The backward LSTM processes the sequence in reverse order, applying the same operations as above but in the opposite direction, and provides output h'_T.

The outputs from the forward and backward LSTMs are combined for "फेसबुक".

BiLSTM can process sequences of varying lengths, making it flexible and robust for diverse text inputs typically seen in multi-label classification tasks.

Fully Connected Layer

A fully connected layer (Chen *et al*., 2021), a dense layer, is one where each neuron or node is connected to every neuron in the previous and subsequent layers. In other words, every neuron in an ultimately linked layer transmits its output to every neuron in the next layer after receiving input from every neuron before it. A fully connected layer usually performs an activation function after calculating the weighted sum of the input data. The weights associated with each connection are learnable parameters that the model adjusts during training to optimize performance on a specific task. The biases are also introduced, allowing the model to account for the offset or shift in the data.

Common activation functions in fully connected layers include Rectified Linear Unit (*ReLU*), sigmoid, and hyperbolic tangent (*tan h*). These activation functions introduce non-linearities, allowing the neural network to model complex relationships in the data.

As for "फेसबुक" in the above review dense layer allows the model to learn an optimal combination of forward state h_T and backward state h'_T:

$$h_T^{Combined} = ReLU(W(h_T, h'_T)) + b$$

where, W and b are learnable parameters and bias.

A final dense layer with 04 units and sigmoid activation is used. Sigmoid activation is used here to predict the probabilities of each of the 04 classes independently.

Results and Discussion

The model is trained and assessed using the dataset after pre-processing. A 70-20-10 ratio divides the dataset into training, validation, and test sets.

Experimental Setup

Python was used to construct the model, and the Keras, Scikit-learn, and TensorFlow libraries were utilized within the development environment that was made available via the Google Colab virtual platform throughout the process. A GPU that is publicly available and 12 gigabytes of random access memory make up the hardware setup. Visualizing and analyzing the results is accomplished by utilizing the matplotlib library.

Each training iteration comprises the processing of 32 samples, which allows for the training process to be fine-tuned. In order to facilitate the optimization of the training process and to avoid overfitting, an early-stopping technique is incorporated. This strategy gives the model the ability to stop training if the validation loss does not improve by a value that is less than three epochs in a row. This prevents the model from being trained for an extended period of time, which is necessary when additional performance improvements are unlikely to occur.

The binary cross-entropy method (Mao *et al*., 2023) is utilized in order to carry out the process of loss estimation for the model. It is possible to overfit by using dropout, an effective regularization strategy (Salehin and Kang, 2023). At each successive layer of training, dropout causes a random skewing of a few neurons.

Performance Metrics Used for Model Evaluation

As a multi-label classification assignment, we model the detection of aspect categories; the averaging function can be used as a micro-average to calculate precision (Plevris *et al*., 2022), recall, and F-score. Precision is the number of correctly predicted aspect categories divided by the total number of aspect category predictions. The number of aspect categories a system successfully predicted divided by the total number of aspect categories is termed as recall. F-score is the harmonic mean of precision and recall. F-score attempts to balance precision and recall. Accuracy is the ratio of correctly classified aspect categories (true positives and negatives) out of the classifier's total number of aspect categories. Note that the calculation ignores instances of the aspect categories that appear more than once in a single sentence.

Results Analysis

We assess the suggested model's performance in terms of its accuracy. The model shows an impressive train accuracy of 93.91%, validation accuracy 84.39% and 0.8345 F-score. This high accuracy and F-score indicate that the model correctly classifies and labels the data. Output for two reviews is shown as follows:

Hindi review – I (Before pre-processing)

फेसबुक का सिक्योरिटी चैकअप फीचर पॉपअप की तरह यूजर्स को दिखाइ देगा।

Hindi review – I (After pre-processing)

फेसबुक सिक्योरिटी चैकअप फीचर पॉपअप यूजर्स दिखाइ देगा

Predicted Multi-label assignment

1 0 0 0

Hindi review – II (Before pre-processing)

इसमें बहुत उच्च स्तर के ग्राफ़िक्स नहीं हैं लेकिन यह गेम बहुत आकर्षित करने वाला है।

Hindi review – II (After pre-processing)

इसमें बहुत उच्च स्तर के ग्राफ़िक्स नहीं हैं लेकिन यह गेम बहुत आकर्षित करने वाला है

Predicted Multi-label assignment

1 1 0 0

Accuracy Analysis

We assess the performance of the suggested BiLSTM model in terms of its accuracy. We plot the training accuracy alongside the validation accuracy as a function of the number of epochs, as shown in Fig. 4a. In order to complete an epoch, the full training dataset must be processed by the model just once. In other words, each and every data point makes a contribution to the parameter update.

There are slight differences in accuracy between training and validation. At first, the model's accuracy rises rapidly as the epochs increase. Later on, it gradually becomes better. It affirms that the model is suitable for the given problem.

Figure 4b displays graphs for the model's loss function, which also provide information comparable to that presented in the previous figure. Regarding the initial stages of the learning process, the validation loss is greater than the training loss. When the model acquires a new aspect category domain feature, the accuracy of the model improves while the validation loss reduces. This is because the model is learning new features. Figure 5 demonstrates that the suggested model accurately detects every aspect category by utilizing high-quality performance measurements. This is demonstrated by the fact that such recognition is accurate. This is the situation that arises when the accuracy has been evaluated for particular domains.

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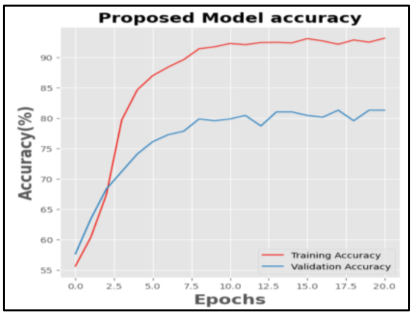

Fig. 4a: Accuracy versus epochs

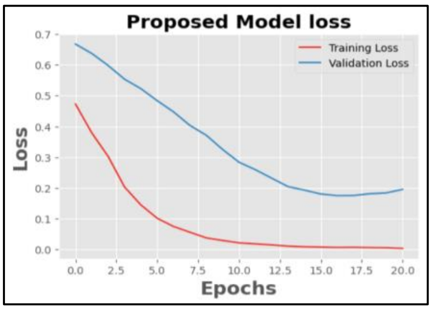

Fig. 4b: Loss versus epochs

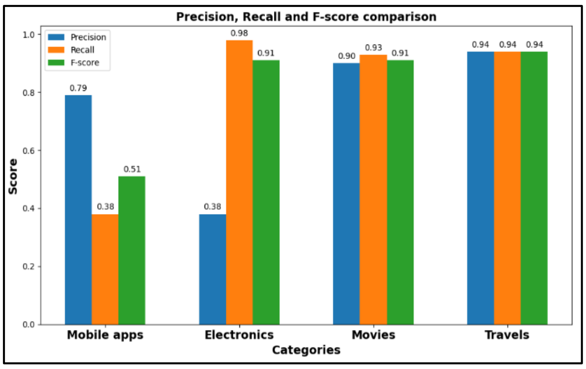

Fig. 5: Aspect category-wise performance concerning precision, recall, and F-score

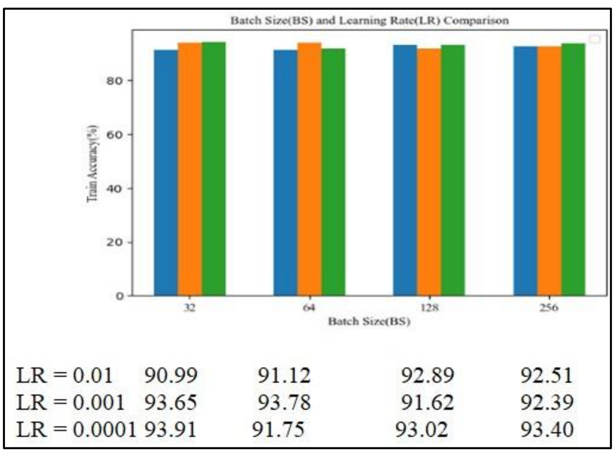

Fig. 6: Accuracy obtained across different mini-batch sizes and learning rates

The model's overall accuracy is 93.91%, and the F-score is 0.8345. The hyper-parameters are specified in Table 3.

Influence of Batch Size and Learning Rate

It is observed that there is a considerable connection between the hyper-parameter Batch Size (BS) and the Learning Rate (LR) of the network. The behavior of the model is explored during the duration of this experiment, and it is done so across a wide range of mini-batch sizes and LRs. The results that were obtained with batch sizes 32, 64, 128, and 256 are presented in Fig. 6. Additionally, the learning rates that were reported were 0.01, 0.001, and 0.0001 accordingly. With an LR of 0.0001 and 32 mini-batches size, the model that is recommended is able to obtain the best possible validation accuracy. When applied to a batch size that is smaller, more accuracy is achieved by the utilization of a lower learning rate.

Comparison of Aspect Category Detection Results

Here, we examine the similarities and differences between the outcomes of our proposed models' aspect category identification and the findings of the current state of the art. When compared to the findings of Akhtar *et al*. (2018); Hetal (2021), the results show that there is a significant improvement. The comparison of the F-scores can be seen in Fig. 7.

Table 3: Dimension and optimal hyper-parameters for the proposed model

Parameter	Description
Maximum length of input	80
LSTM units	25
Dropout rate	0.5
Number of neuron units in dense layer	50
The function of the activation function	ReLU
Number of neuron units in output layer	04
The function of activation	Sigmoid
Epochs	33
Mini-batch size	32
Rate of learning	0.0001
Rate of dropout	$5.0X10^{-1}$

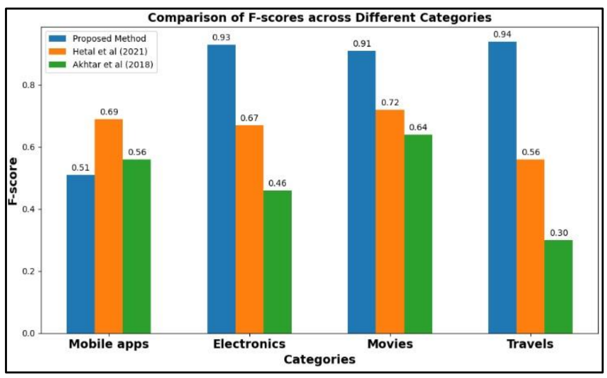

Fig. 7: F-score comparison of the proposed model with state-of-art results

through the utilization of the BiLSTM model suggested, we are able to accomplish the goal of achieving a maximum F-score value of 0.94 for the Travels. When compared to the findings considered to be state-of-the-art for Hindi, the F-scores for all three domains, with the exception of the Mobile apps domain, exhibit an improvement from a range of 0.19 to 0.64. It is important to note that the Mobile apps domain deviates from this trend. The F-score value of 0.51 indicates that the Mobile apps aspect category did not demonstrate any significant growth throughout the course of the study. The fact that there are fewer occurrences (201) of the Mobile apps domain, as demonstrated in Table 2, could be one of the possible reasons for this particular phenomenon. Within the Electronics, Movies, and Travels aspect category, the model obtains a significant improvement in its F-score compared to its previous score.

Conclusion and Future Work

Within the framework of the proposed deep BiLSTM model aspect types are being recognized. An aspect category is a generalization of the characteristics that are addressed in a review, which is a presentation of the numerous features. A review is a presentation of several features. Specifically, the problem can be found within the framework of the paradigm of multi-label categorization. The model has an outstanding F-score of 0.8345 and train accuracy of 93.91 and 84.39% test accuracy across four domains, which is higher than the results that are considered to be state-of-the-art for Hindi. In addition, the model has a high accuracy rate. It is possible for the model to achieve an acceptable balance between the F-score and the accuracy measurements. BiLSTM is able to successfully handle sequences of variable lengths, which a significant advantage is given the broad range of lengths that are present in Hindi phrases. The complex relationships that exist between the words in the sentences are successfully captured by the BiLSTM units. In the event that the dataset was larger and contained a greater number of domains that involved the combination of hand-crafted qualities, it would be possible to do more in-depth testing on the approach that has been proposed. We believe that this will result in an improvement in the performance of the model.

We are looking forward to improving performance by putting into action techniques that are founded on the concept of transfer learning, employing ensemble methods i.e. combining the prediction of multiple models to leverage their complementary strengths. Enhancing models that can handle multiple languages or transfer knowledge between languages can expand the applicability to a global scale.

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Author’s Contributions

Ashwani Gupta: Carrying out the tests, recording the findings and analysis, and compiling the report.

Utpal Sharma: Supervision and direction for the presentation and experiments as a whole.

Ethics

This manuscript substance is the authors' own original work and has not been previously published somewhere else.

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