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Expert Approach for Trio Awareness-Based Framework for Automatic Image Captioning Using Visual, Semantic Attention Mechanisms, and HES

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ABSTRACT

Image captioning is the process of analysing the contents of an image and changing them into a coherent Language to explain the image. According to neuroscience research human vision and language formation are connected together. Even if there are many techniques for image captioning, including template filling, and content retrieval, the deep learning-based methods are most popular in current scenario. Feature vectors are generated from an image using an image encoder through the deep learning techniques, and these feature vectors are transformed into a string of words by a language decoder. Various CNNs such as VGG16, VGG19, Inception, and ResNet are available for extracting image features. Various experiments have been performed to find out the best encoder for the purpose of image captioning. LSTM and GRU are two most recently used decoders to generate captions. GRU is the latest version of RNN. It is much faster than LSTM as compared to computational efficiency. Using the encoder-decoder approach or simple attention-based mechanisms has not provided very efficient results. So, visual attention as well as textual attention have been used for efficient image captioning. There are various visual attention mechanisms such as grid-based attention and region-based attention to specifically retrieve image features, and these features are used as additive attention to the decoder. For textual attention, word embedding have been used. In the proposed framework, a trio awareness-based mechanism has been utilized. The objective of this research is to extract Visual characteristics from the region of interest (RoI) of an image and text features using the GloVe embedding technique. The ResNet version of the Convolutional Neural Network (CNN) is utilized as an encoder. A Gated Recurrent Unit (GRU) is utilized as the decoder, and the Human Evaluation Score has been incorporated as a third parameter to further validate the model's performance. The proposed model is tested on the Flickr8k dataset, the findings show that the results attained through the proposed mechanism are more accurate than those of other models

1. Introduction

Social media generates massive images daily from advertisements, the internet, image posting, figures, etc. The viewers must interpret the visuals in these sources for themselves. Although most photographs lack a description, most people can still grasp them without the help of their in-depth subtitles. Robots generate automatic image captions for the general public. Automated tasks that produce image descriptions are called Generations of Image Captions. They include understanding the semantics of the image, which necessitates understanding the main objects, their attributes, locations, and interactions within images. Subtle semantic connotations must also be deduced to generate proper captions. Subtitles can be of different types, such as image captions and video captions.

1.1 Explanation of Image Captioning

Image captioning is the process of taking an image's characteristics and turning them into a coherent statement. It is useful for various motives. For example, image captioning could help those who are blind or visually impaired if technology could be created that could take an image, convert it into text, and then produce sound in light of these writings. An example of its use is in image indexing. Social media sites like Facebook and Twitter can use photographs to tell stories. These reports can go into further detail about our activities, dress, and venue (beach, cafe, etc.) [1].

1.1.1 Understanding the Images

Computer vision (CV) is a subfield of artificial intelligence that allows computers to extract meaningful data from images. It is equipped with every tool needed to extract the necessary data from the pictures [2]. A great deal of research is done in the domains of CV, namely in the fields of recognition and perception of images. An image captioning system must correctly identify many entities. For instance, edges, colors, and contour and geometric lines are examples of typical features. In general, hand-crafted qualities are computationally expensive and not very robust. Therefore, it is impossible to extract handcrafted traits from a lengthy and intricate succession of images. Systems that use Deep Learning Techniques (DLTs) automatically learn features [3][4]. Sound spectrograms are handled by convolution neural networks (CNNs), a kind of deep neural network structure used in image, video, and speech processing applications.

1.1.2 Overview of Natural Language

An image captioning system must correctly identify a large number of items. Typical qualities include shapes, colors, edges, and lines that are geometric in nature. Handcrafted characteristics are typically less reliable and more computationally expensive. As a result, it is hard to distinguish handcrafted elements from a large and complex photo series. Deep learning methods (DLTs) enable systems to learn features automatically [3]. Convolution neural networks (CNNs), a type of deep neural network architecture utilized in image, video, and audio processing applications, are capable of handling sound spectrograms.

1.2 Deep Learning-Based Image Captioning

The introduction of DLTs in 2006 was motivated by the way neurons behave in the human brain. These are sometimes referred to as Deep Neural Networks (DNNs) due to their breakthrough in neural network construction. The development of neural networks has radically altered the way problems are solved [5]. Since the neurons are interconnected, they learn from each other and from the information supplied into the network. They learn about data trends and patterns so they can recognize them when they appear in fresh or pertinent data. In a neural network, a neuron is the smallest unit in which the majority of computation takes place. Neurons store the individual components of the data by varying their weights in accordance with the patterns in the input. These characteristics work together to forecast requirements [6]. An input layer, multiple hidden layers made of these neurons stacked on top of each other, and an output layer for output prediction make up the network as a whole.

There are three types of layers in a neural network:

i. **Input layer:** This is the layer where we provide input to the model. The total number of features (or pixels in the case of images) in our product equals the number of neurons in the layer.
ii. **Hidden layer:** The hidden layer receives input from the input layer. There may be many hidden layers depending on the value of the data and our model. The number of neurons per hidden layer varies but is generally larger than the features. This network is nonlinear because the output of each layer is calculated by multiplying the previous layer's output by the learned weight operation, adding the uncertainty, and then using the activation function.

iii. **Output layer:** Next, a logistic function (such as Sigmoid or SoftMax) is fed to the output of the latent process and the output of each category is converted into a function for that category.

1.2.1 CNN Architecture

CNNs are created by transforming multiple layers of sensors into fully connected networks [7]. CNNs exploit the hierarchical structure of data by combining smaller, simpler patterns into larger patterns that are printed on filters.

i. **Input Layer:** This is the layer where we give input to the model. Usually, an image or an image of an image is entered into the CNN.

ii. **Convolutional Layer:** The convolutional layers are used to extract features from input data, such as images. It applies a collection of learned filters to the input image. The filter/kernel size is usually a 2x2 or 3x3 or 5x5 matrix. As it moves through the data, it calculates the product of the weighted product and compares the image block of images. The feature map is the result of this layer. Forward propagation creates an image representation of the receptive field by allowing the kernel to slide across the height and width of the image. This creates a two-dimensional functional map that represents the image and provides the response of the nucleus at each location. The word "step" refers to the sheer size of the core [8]. If we have the ideas of size *W x W x D*, *Dout* area width *F*, and number of cores with pitch *S* and padding *P*, we can use these formulas to calculate the size of the volume. Then size of the output volume will be $W_{OUT} * W_{OUT} * D_{OUT}$ as shown in Eq.(1).

$$w_{OUT=\frac{w-F+2P}{s}+1} \quad \textbf{Eq. (1)}$$

iii. **Activation Process:** A layer activates a negative impact on the network by connecting the activation function to the output of its previous layer. It will output the convolution process and use the optimization tool. Intensifiers such as *Sigmoid*, Rectified Linear Activation Unit (*ReLU*), *Tanh* and *SoftMax* are frequently used.

   a. **Sigmoid Activation Function:** This function provides the output between 0 and 1. It is highly useful for cases where the output is desired in terms of probability. The formula is shown in Eq.(2).

$$f(z) = \frac{1}{1+e^{-z}} \quad \textbf{Eq.(2)}$$

   b. **Tanh Activation Function:** It is also like the sigmoid activation function but its range varies from -1 to 1. Like the Sigmoid function, it is also used in feed-forward networks.

   c. **Rectified Linear Unit Activation Function:** It provides the output as 0 in case of input is less than 0, otherwise, it provides the same input value.

   d. **SoftMax Activation Function:** It is used as a transfer process to distribute the input into different categories.

iv. **Pooling Layer:** The pooling layer is usually added after the convolution layer. It is used to minimize the spatial dimensions of the function maps. There are various pooling layers such as maximum pooling, average pooling, and global pooling. In the case of the maximum pooling, the highest number is taken out of each block, while in the case of the average pooling, the average value is taken out of the block.

v. **Flattening Layer:** Flattening is a layer where you convert all the resulting 2D matrices into a single long continuous linear vector. This layer connects the convolutional network with the fully connected layer.
vi. **Fully Connected Layer:** The fully connected layer learns global patterns in its input function. The weights in this layer are the same as in neural networks. Each neuron is connected to every other neuron, hence its name.

1.2.2 LSTM

LSTM is the extended form of RNN. In order to address the vanishing gradient problem and resolve long-term dependency issues in RNN, the LSTM is utilized [9]. It can maintain the historical data used in RNN. These long-term dependencies are preserved and learned through the use of the memory cell, the basic unit of the LSTM. Three gates make up an LSTM cell: an input gate, an output gate, and a forget gate. These gates adjust the cell state in accordance with the input received.

i. **Input Gate:** This gate is used to determine what information to be input to the memory cell.
ii. **Forget Gate:** This gate is responsible for deciding which information should be discarded.
iii. **Output Gate:** This gate is utilized to compute the subsequent hidden state.
iv. **Cell Gate:** This is used to find the present state of the memory cell

2. BACKGROUND AND RELATED WORKS

Many approaches are there to generate automatic image captions for a given image. The earlier approaches include content retrieval and template filling-based methods. The recent approaches are based on deep learning mechanisms. These approaches include the neural networks to generate captions based on image features. These approaches are discussed in this section. Traditional approaches to image captioning, such as template-based and retrieval-based methods, trusted deeply on predefined sentence structures or matching images to pre-existing captions in large databases. While these methods were effective to some extent, they lacked the flexibility and adaptability required for generating accurate captions for a wide variety of images. In recent years, deep learning-based methods have revolutionized image captioning. These approaches typically involve two main components: an image encoder and a language decoder. The encoder, often a Convolutional Neural Network (CNN) such as VGG16, VGG19, Inception, or ResNet, is used to extract feature vectors from the image. The decoder, usually a Recurrent Neural Network (RNN) variant like Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU), then generates a sequence of words that form a coherent caption based on the extracted features. Anderson et al. [10] introduced a bottom-up and top-down attention mechanism that allows models to focus on specific objects and regions in an image, leading to more detailed and accurate captions.

2.1 Encoder-Decoder Based Approaches

Image captioning is done using encoder-decoder techniques by mapping the input data to an output sequence. The image is used as input to the encoder, and feature vectors are generated. To generate automatic image captions, an encoder-decoder approach was presented by Vinyals et al. [11]. A CNN based encoder and RNN based decoder is used in this approach. A LSTM-based decoder has been used to generate captions. Another approach using a combination of CNN and RNN has been proposed by Donahue et al. [12]. In this approach, a visual input is taken from a CNN-based architecture and passed to an RNN for sentence generation. A deep learning-based approach for image captioning is proposed by Karpathy and Fei-Fei [13]. In this approach, a multimodal

recurrent neural network is used to generate image captions. The approach uses a CNN-based encoder and a bidirectional RNN-based decoder. Another encoder-decoder-based approach for image captioning is presented by Johnson et al. [14]. The approach uses a combination of CNN and RNN. The encoder is a CNN-based architecture and the decoder is a RNN-based architecture. The approach uses a visual semantic embedding model to generate captions. Yang et al.[15] proposed a model that utilizes ResNet as an encoder and GRU as a decoder, demonstrating improved performance on benchmark datasets like Flickr8k.Wang et al.[16] explored the use of GRU as a decoder in combination with various CNN encoders, highlighting its advantages in computational efficiency. Zhang et al. [17] investigated the impact of different CNN architectures, including VGG16, VGG19, and Inception, on image captioning accuracy. Huang et al. [18] compared the performance of LSTM and GRU as decoders, concluding that GRU offers faster and more computationally efficient caption generation. Li et al. [19] investigated the use of ResNet as an encoder for image captioning, demonstrating its superior performance in feature extraction compared to other CNN architectures Vinyals et al. [20] proposed a deep learning framework combining CNNs with LSTM decoders, highlighting the effectiveness of sequence-to-sequence models in generating coherent captions.

2.2 Attention Based Approaches

Attention mechanisms are focused on target portions of the image at the time of generating captions. These mechanisms help to increase the quality of the image captioning models. An approach using attention mechanism for image captioning is proposed by Xu et al. [21]. The approach uses a combination of CNN and RNN. The encoder is a CNN-based architecture and the decoder is a RNN-based architecture. The approach uses a visual attention mechanism to focus on target portion of the image while generating captions. Another approach using attention mechanism for image captioning is proposed by Lu et al. [22]. The approach uses a combination of CNN and RNN. The encoder is a CNN-based architecture and the decoder is a RNN-based architecture. The approach uses a co-attention mechanism to emphasis on both visual and textual features while generating captions. Sun et al. [28] introduced a trio awareness mechanism that combines visual, textual, and evaluation-based attention for enhanced image captioning. Lin et al. [23] proposed an attention-based framework that integrates RoI features with GloVe embeddings for more accurate and contextually relevant captions. Johnson et al. [24] proposed a region-based attention mechanism that focuses on the most salient parts of an image, improving the quality of the generated captions. Wu et al. [25] introduced a hybrid attention model that combines visual and textual attention for more accurate image captioning. Xu et al. [26] explored the use of attention mechanisms in image captioning, focusing on how grid-based and region-based attention can improve feature extraction and caption accuracy.

2.3 Reinforcement Learning Based Approaches

Reinforcement learning-based methods are used to increase the performance of image captioning models. These methods use a reward mechanism to increase the quality of the generated captions. An approach using reinforcement learning for image captioning is proposed by Rennie et al. [27]. The methodology uses a combination of CNN and RNN. The encoder is a CNN-based architecture and the decoder is a RNN-based architecture. The approach uses a self-critical sequence training mechanism to increase the quality of the generated captions. Another approach using reinforcement learning for image captioning is proposed by Liu et al. [28]. The approach uses a combination of CNN and RNN. The encoder is a CNN-based architecture and the decoder is a RNN-based architecture. The approach uses a policy gradient mechanism to improve the quality of the generated captions.

3. Proposed Work

The proposed work aims to develop a trio awareness-based framework for automatic image captioning using visual, semantic attention mechanisms, and human evaluation score. To extract visual features from the region of interest (RoI) in an image and text features using the GloVe embedding technique is the main objective. The ResNet version of the Convolutional Neural Network serves as the encoder, gated recurrent unit as a decoder , and the Human Evaluation Score has been incorporated as a third parameter to further validate the model's performance. Chen et al. [29] applied GloVe embeddings to enhance textual attention mechanisms, improving the contextual relevance of generated captions.

3.1 Visual Attention Mechanism

The visual attention mechanism is used to focus on specific parts of the image while generating captions. The mechanism helps to improve the performance of the image captioning model by focusing on the most relevant parts of the image. The visual attention mechanism used in this work is based on the grid-based attention mechanism. The image is divided into a grid of smaller regions, and attention weights are assigned to each region. The attention weights are calculated based on the relevance of each region to the generated caption.

3.2 Semantic Attention Mechanism

The semantic attention mechanism is used to emphasis on specific portions of the text while generating captions. The mechanism helps to improve the performance of the image captioning model by focusing on the most relevant parts of the text. The semantic attention mechanism used in this work is based on the word embedding technique. The GloVe embedding technique is used to generate word embedding for the text. The attention weights are assigned to each word based on the relevance of the word to the generated caption.

3.3 Human Evaluation Score

The Human Evaluation Score (HES) is used as a third parameter to further validate the model's performance. The HES is calculated based on the quality of the generated captions. The score is assigned by human evaluators based on the relevance, fluency, and coherence of the generated captions. The HES helps to ensure that the generated captions are of high quality and are relevant to the given image.Gao et al. [30] developed a comprehensive evaluation framework for image captioning models, incorporating HES as a key metric for assessing caption quality. Tan et al. [31] developed a model that incorporates human evaluation scores as an additional metric for assessing caption quality, demonstrating its effectiveness in improving model performance.

4. Description:

This Paper introduces a deep learning system based on the Trio Awareness Mechanism, where the encoder and decoder, respectively, are subjected to both visual and textual attention. Although there have been numerous deep learning-based frameworks developed, including textual attention-based, semantic-based, and visual attention-based frameworks, the suggested framework combines these methods into a unified Trio Awareness Mechanism. GRU and ResNet50 are employed in this system, respectively, as the encoder and decoder. GloVe embedding for word representations and region-based visual attention have been applied. The GRU has provided better results compared to LSTM in the role of the decoder. GloVe embedding focuses on the semantic purpose of the words, resulting in improved BLEU scores as well as other evaluation metrics such as METEOR and ROUGE. The incorporation of the HES Human Evaluation Score ensures that the quality of the generated captions is assessed

through human judgment, providing a comprehensive evaluation alongside automated metrics. This holistic approach validates the effectiveness and practical applicability of the proposed framework

5. Architecture and Methodology:

The architecture proposed in this research aims to focus the development environment to a deep learning system based on the Trio Awareness Mechanism, where the encoder and decoder, respectively, are subjected to both visual and textual attention. Although there have been numerous deep learning-based frameworks developed, including textual attention-based, semantic-based, and visual attention-based frameworks, the suggested framework combines these methods into a unified Trio Awareness Mechanism. GRU and ResNet50 are employed in this system, respectively, as the encoder and decoder. GloVe embedding for word representations and region-based visual attention have been applied. The GRU has provided better results compared to LSTM in the role of the decoder. GloVe embedding focuses on the semantic purpose of the words, resulting in improved BLEU scores as well as other evaluation metrics such as METEOR and ROUGE. The incorporation of the HES Human Evaluation Score ensures that the quality of the generated captions is assessed through human judgment, providing a comprehensive evaluation alongside automated metrics. This holistic approach validates the effectiveness and practical applicability of the proposed framework.

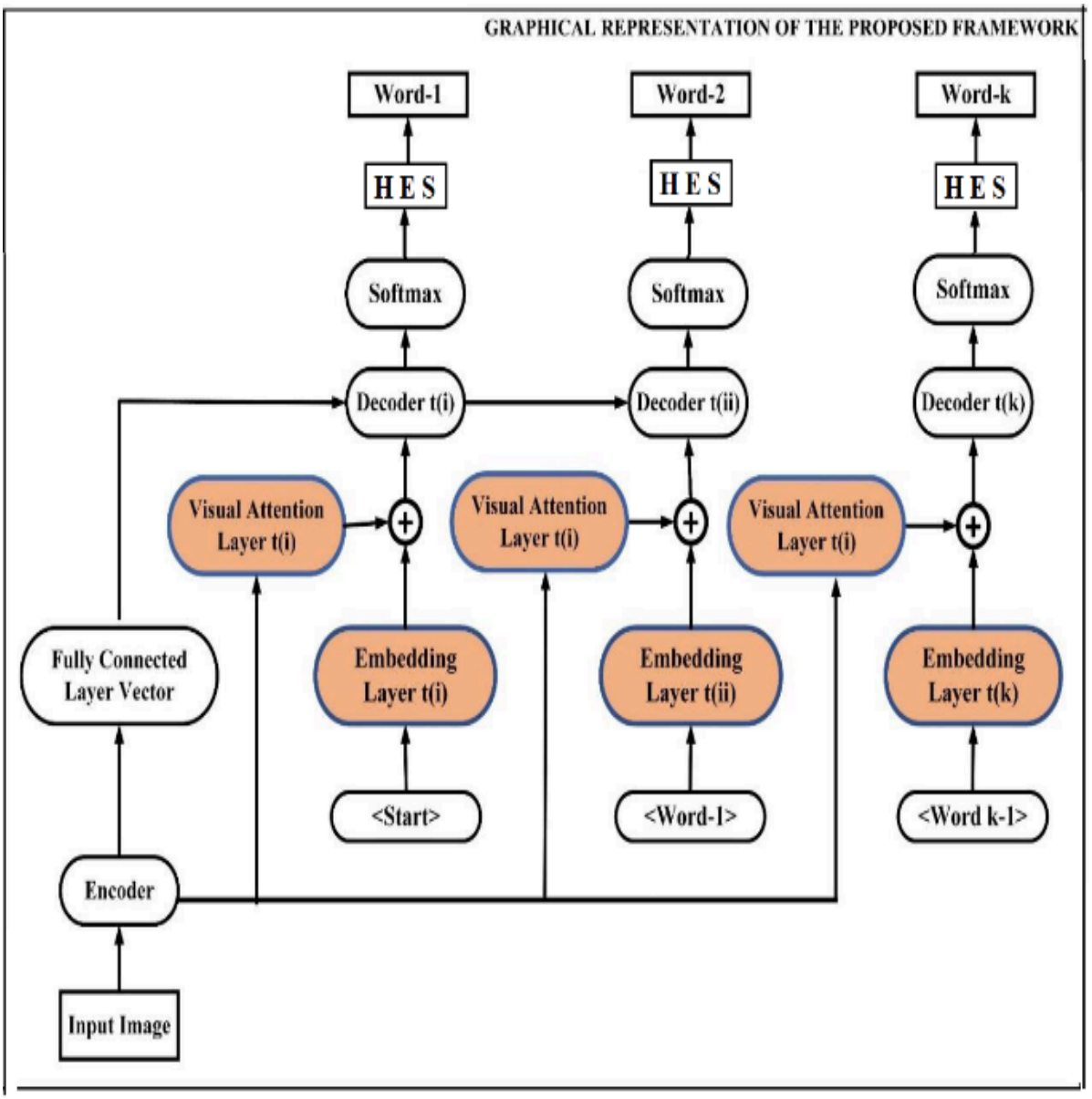

Fig. 1 Trio awareness deep learning based image captioning model

The following stages outline some significant points that highlight the proposed framework:

i. ResNet50 is used as a convolutional neural network.
ii. Region of Interest is identified for highly visual enhanced features.
iii. GloVe embedding method is used to extract text-based semantic features.
iv. A Gated Recurrent Unit serves as a decoder.
v. Experiments have been conducted using Jupyter Notebook.
vi. The HES (Human Evaluation Score) is incorporated to assess the quality of generated captions based on human judgment.

The proposed model utilizes an encoder to process an image as input. The encoder is implemented using ResNet50, a deep convolutional neural network. The final fully connected layer of the encoder produces a feature vector that encapsulates the general details of the image. However, this feature vector alone is insufficient to capture the important and specific details of the image. The proposed

model integrates a visual attention mechanism, which allows the model to emphasis on different regions of the image at each time step, thereby extracting more specific and relevant features for caption generation. The framework, illustrated in Figure.1, is tested on the Flickr8k dataset, demonstrating highly effective results. The process begins with a <start> token, which, along with embedding information and region-based features from the encoder, is input to the GRU (Gated Recurrent Unit). At the first time step (t=1), the GRU generates the first word of the caption. Subsequently, at each following time step (t=i), the output word generated in the previous step is used as the input word, and the same process is repeated. The visual attention layer at each time step focuses on different parts of the image, enhancing the relevant feature information used by the GRU. The generated word is then processed by the SoftMax activation function to produce the next word in the sequence. After the SoftMax layer, the generated word is evaluated using the Human Evaluation Score (HES). Human evaluators assess the quality of the generated word based on criteria such as relevance, fluency, descriptiveness, and coherence. The HES for each word is incorporated into the model to ensure that the generated captions are of high quality according to human judgment. This iterative process continues until a specific stopping criterion is met, such as the generation of an <end> token or reaching a predefined maximum number of words. The incorporation of HES at each step ensures that the generated captions are continuously evaluated and refined based on human feedback.at each time step t=i (where i ranges from 1 to k), the total of i-1 generated words, combined with the embedding and visual attention-enhanced image features, are fed into the decoder to produce the next word. The generated word is then evaluated using HES, and this process ensures that the generated captions are both accurate and descriptive, leveraging the combined power of ResNet50 for feature extraction, GRU with attention for sequential word generation, and HES for quality assessment.

6. Implementation

The proposed model is tested on the Flickr8k dataset. The dataset contains 8000 images, each with five corresponding captions. The dataset is separated into training, validation, and test sets. The proposed model is trained on the training set and evaluated on the test set. The evaluation metrics like BLEU, METEOR, and ROUGE are used to check the performance of model. The results achieved through the proposed framework are highly effective.

6.1 Evaluation Metrics

The performance of the proposed model is evaluated using the following evaluation metrics:

i. **BLEU:** The Bilingual Evaluation Understudy score is a metric.it estimate the quality of the generated captions. BLUE compare generated caption with the reference captions to evaluate precision. The range of BLUE score is in between 0 and 1.high score shows good performance.
ii. **METEOR:** The METEOR score is a metric used to evaluate the quality of the generated captions. It measures the precision and recall of the generated captions by comparing them to the reference captions. The range of METEOR score is in between 0 and 1.high score shows good performance
iii. **ROUGE:** The ROUGE score is a metric used to evaluate the quality of the generated captions. It measures the recall of the generated captions by comparing them to the reference captions. The range of ROUGE score is in between 0 and 1.high score shows good performance**.**

6.2 ResNet50

ResNet requires inputs that are 224 × 224 RGB pictures in size. The ResNet50 Convolutional

Neural Network is employed in the proposed model to extract features from the input image. The ResNet50 architecture outperforms the VGG16 and VGG19 on the ImageNet object detection problem. With the help of ResNet50, features are extracted from fully connected layer, which creates the vector F that contains the overall information about the image as shown in Eq.(3)

$$F = ResNet(I) \qquad \textbf{Eq. (3)}$$

Here, F is a vector that is produced from the last convolutional layer of the CNN. This is fully connected layer and contains the overall information of the image. But it may not provide semantically and region wise strong information. Guiding information has been generated with the fusion of visual features based on region of interest using encoder and text features using GloVe word embedding method. The HES component evaluates the generated word and provides feedback to refine the model's predictions. This feedback helps in adjusting the word probabilities, making sure that the generated captions are of higher quality.

6.3. GRU

A form of RNN is LSTM. Because it addresses the problems with basic RNN, it is superior to simple RNN. Exploding gradient, disappearing gradient, and long-term dependency are two of the main problems that simple RNN encounters. GRU is a more recent iteration of Recurrent Neural Network (RNN), which was created in 2014 and is rapidly gaining popularity. Traditional RNN has an issue with short-term memory. There may be instances where an autocomplete of an unfinished sentence is necessary. But since traditional RNN has short-term memory problems, it may not offer the precise solution to the same problem if it is used to solve it. GRU and LSTM neural networks are capable of handling these tasks. LSTM and GRU are two unique RNN subtypes. As GRU is lighter version of LSTM, the proposed model has used GRU as a decoder. GRU eliminates the RNN's gradient problem and is very beneficial for applications involving sentence production. Short-term memory and long-term memory are combined in GRU's hidden state. While the update gate of GRU understands how much of the past memory to preserve, the reset gate knows how much of the past memory to forget. When captioning an image, GRU uses an input vector from CNN that represents the features of the image and creates the caption for the one that has been provided. The suggested model provides the GRU with an input feature vector along with guiding information which is the fusion of region based visual features and semantic features from similar images. By using these data and an initial word, GRU predicts one word at a time and at next iteration this output word is used as an input word. The GRU works as per the below Eq.(4)

$$h_t = GRU(X_t, h_{t-1}) \qquad \textbf{Eq.(4)}$$

Here X_t is the input vector and $h_t - 1$ is the previous hidden state. The internal mathematical equations of the GRU are as follows:

$$Z(t) = \sigma(W_Z.\, X_t + U_z.\, h_{t-1} + \beta_{update}) \qquad \textbf{Eq.(5)}$$

$$R(t) = \sigma(W_R.\, X_t + U_r.\, h_{t-1} + \beta_{reset}) \qquad \textbf{Eq.(6)}$$

$$h' = tanh(W_h.\, X_t + R(t) * U_h.\, h_{t-1} + \beta_{update}) \qquad \textbf{Eq.(7)}$$

$$h = Z(t) * h_{t-1} + (1 - Z(t)) * h' \quad \textbf{Eq.(8)}$$

Initially at $(t - 1)$ time step, pointwise multiplication takes place between update gate vector and hidden state, while the same operation is performed between input vector and the update gate weight vectors. The bias vector is multiplied with the guiding information vector and is combined with these two other vectors. At next time step (t), as specified in Eq.(7), the total result is subjected to the sigmoid function to produce a new update vector. One pointwise multiplication takes place between weight vector of reset gate and input vector. The multiplication of guiding information vector and bias vector is then added in addition to these two vectors. As demonstrated in Eq.(6), an activation function (sigmoid function) is applied to the overall outcome to produce a new vector for reset gate at every time step (t). The gate vector is updated and reset for time step (t). A pointwise multiplication takes place between weight vector of hidden state and input vector. Pointwise multiplication of the update vector and regular multiplication of the recently created reset vector are applied to the concealed state vector. The outcome is included in the multiplication of guiding information vector and bias update vector. According to Eq.(7), it creates a somewhat new hidden state or output state. The update vector's negation is multiplied by this moderately created hidden state. Update vector is aggregated by the previous concealed state. As demonstrated in Eq.(8), these two different vectors are combined to produce the GRU's output at time step (t). The new hidden state is also the output at time step t. GRU creates a new word that serves as a new input for the following time step using the input word and initial hidden state. Until the final caption is produced or the word limit is met, this process is repeated.

6.4 Visual Enhancement and Semantic Features Extraction:

Region based features are extracted by CNN using RoI segmentation. First, the difference of Gaussian (DoG) technique detects the initial important key points. The mathematical process for DoG is shown in Eq.(9)

$$F(x, y, \sigma, k) = M(x, y, \sigma k) - M(x, y, \sigma) \quad \textbf{Eq.(9)}$$

The image's pixel coordinates are (x, y), and the standard deviation of the normal distribution is σ. k is a multiplicative constant whose value is approximated to 1.4 for calculation purposes. Two-dimensional convolution function for each image is calculated using Eq.10 and the calculation of (x, y,) is shown in Eq. (11)

$$M(x, y, \sigma) = H(x, y, \sigma) * i(x, y) \quad \textbf{Eq. (10)}$$

$$H(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{\frac{x^2+y^2}{2\sigma^2}} \quad \textbf{Eq. (11)}$$

Now, only dense points are saved and the rest are discarded using a filtering technique. Based on the number of key points, a threshold value is decided in between 1 and 5. Now statistic function is applied on each key point and output is compared with the threshold value. If output is larger or equal than the threshold value then it is kept as 1 otherwise it is kept as 0. Now, key points having value as 1 are dense points and are stored for further processing of finding the region of interest. The left and right boundaries are obtained using these dense key

points and visual enhancement region is obtained.

6.5 GloVe embedding:

GloVe embedding is the most qualitative approach for word embedding. This approach is used to represent the semantic relationship between the words. The main key benefit of using this approach is that it provides low computational cost due to least error function or square root. Table 1 shows the semantic representation matrix using GloVe embedding. Consider the documents as:

i. Computer Vision Programming Language

ii. Programming Language Computer Science

Table 1: semantic representation matrix using GloVe embedding

	Computer	**Vision**	**Programming**	**Language**	**Science**
Computer	0	1	0	1	1
Vision	1	0	1	0	0
Programming	0	1	0	2	0
Language	1	0	2	0	0
Science	1	0	0	0	0

The above matrix is the co-occurrence matrix which shows that how much context of a word is present in respect of another word. Here, 0 means the words have never come adjacent to each other in the entire documents. Similarly, the other values like 1,2,3 and so on represent the adjacency between words that can be used to check the context or semantic relations between the words. The Eq. (12), (13) and (14) shows the process of generating co-occurrence matrix using GloVe embedding which is used for semantic representation between words.

$$p\left(\frac{y}{x}\right) = probability\ (y\ in\ context\ of\ x) \qquad Eq.\ (12)$$

$$Mathematically,\ p\left(\frac{y}{x}\right) = \frac{m_{xy}}{m_x} \qquad \textbf{Eq.(13)}$$

Where, m_{xy} is the co-occurrence matrix[x][y], and

$$m_x = \sum_{1}^{k} m_{xk} \qquad \textbf{Eq.(14)}$$

- $P(x/k)/P(y/k)$ **will be equal to 1, if word k is either related to both x**

and y or unrelated to both.

- **P(x/k) / P(y/k) will be less than 1, if word k is related to y but not related to x.**
- **P(x/k) / P(y/k) will be greater than 1, if word k is related to x but not related to y.**

In the proposed framework, GloVe embedding technique has been used as word representation method as it has efficient semantic relationships feature.

7. Results

The most popular datasets for image captioning are Flickr8K, Flickr30K, and MSCOCO. Each of the 30,000 photos in the Flickr30K collection has five subtitles. The 30K photos in Flickr30K have 1,50,000 captions altogether. Each of the eight thousand photos in the Flickr8K collection has five captions. The photos in the Flickr8K dataset have 30,000 captions in total. These datasets are quite good at captioning photos and contain examples from many different categories. Pictures are chosen from the databases and used for validation, testing, and training. Flickr8K is the dataset that the model in this study was built with. Out of all the 8,000 images, 6,000 were utilized for training. The first 1,000 images were used for testing, while the remaining 1,000 were used for validation. However, the captions have been pre-processed so that words that might no longer be useful in creating better sentences for the search photos have been ignored. For image captioning purposes, a variety of evaluation metrics are utilized. The model has been assessed in this study using the BLEU, METEOR, ROUGE, and CIDEr scores. The BLEU score measures how closely the generated and referenced captions match. The BLEU score ranges from 0 to 1. Scores of 0 indicate no matching between the generated and referred captions, whereas scores of 1 indicate complete word matching.

The generated and referred captions' word or grammatical unit correspondence is shown by the BLEU-1 score. The other BLEU scores do the same thing by calculating how well n words match the created and referenced captions. The METEOR evaluation measure's primary goal is to focus on word synonyms. The BLEU score by itself is insufficient to assess the quality of the generated caption. Two additional measures that have been looked at and are included in the final matrix are CIDEr and ROUGE. Furthermore, a full assessment based on human judgment is provided by the incorporation of the HES (Human Evaluation Score), which guarantees that the generated captions are assessed for relevance, fluency, accuracy, and innovation.

Table 2 shows the trial results for the model with the Flickr8K Dataset and HES.

Table 2: Trial results for the model with the Flickr8K Dataset and HES.

	BLEU-1 (%)	**BLEU-2 (%)**	**BLEU-3 (%)**	**BLEU-4 (%)**	**METEOR (%)**	**ROUGE-L (%)**	**HES (%)**
ResNet50 and LSTM	73.8	61.8	50.8	41.9	36.5	60.4	82.1
Inception V3 and GRU	73.1	60.1	49.6	41.5	36.1	60.1	81.7

ResNet50 and GRU With visual Attention	74.2	61.8	50.8	41.9	37.2	60.5	83.2
Double Attention Model: Combine Sentence and Word Level Attention	71.3	52.8	38.3	27.2	23.5	51.2	75.3
NICNDA (Dual Attention Mechanism)	74.1	61.4	50.9	42.3	35.0	60.2	80.8
Proposed Model (Trio Awareness-based Mechanism)	**78.2**	**63.1**	**52.8**	**44.9**	**39.2**	**62.5**	**86.7**

The suggested model for image captioning has produced superior outcomes to a number of other current models. ResNet50 and Inception V3 encoders and GRU decoder along with the Trio Awareness Mechanism are used to test the proposed model. When compared to other existing models, the suggested model produced better results. The Trio Awareness Mechanism was employed in the proposed model. In order to better grasp visual attributes and generate image captions, region-based visual features have been applied. For the suggested model, ResNet50 is employed as an encoder and GRU as a decoder. The proposed model (ResNet50 and GRU) together with the Trio Awareness Mechanism outperformed the visual attention model (ResNet50 and GRU) in terms of BLEU scores, other automated assessment metrics, and the HES for image captioning. High accuracy indicates that a caption reference is almost certain. The experiments in this research were carried out utilizing the Flickr8K dataset. The BLEU scores for the ResNet50 and GRU-based model with visual attention are 74.2%, 61.8%, 50.8%, and 41.9% for BLEU-1, BLEU-2, BLEU-3, and BLEU-4, respectively. The proposed model, which combines a trio awareness mechanism with a ResNet50 encoder and GRU decoder, has been found to produce the best outcomes among all these models. The BLEU scores for the proposed model are 78.2%, 63.1%, 52.8%, and 44.9% for BLEU-1, BLEU-2, BLEU-3, and BLEU-4, respectively.

Figure 2 and 3 shows the comparative analysis of Trio awareness based proposed model with other existing deep learning models using column graph and line graph respectively In addition to BLEU scores, the suggested methodology has improved results for other evaluation measures like METEOR, ROUGE-L, and Human Evaluation Score (HES). On the Flickr8K dataset, the proposed approach is used to produce some samples of image captions. The generated sentences are grammatically and semantically sound, and the captions are quite pertinent to the photographs. Figure 4 shows the image caption generation using the proposed model.

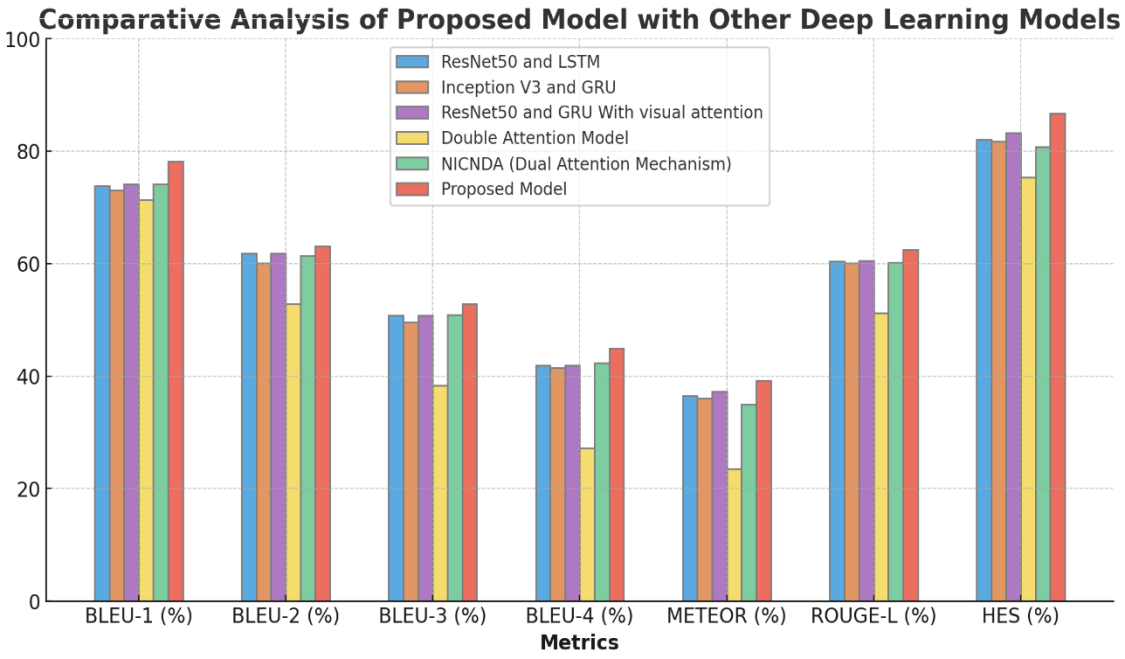

Fig 2 Analysis of Various Models in a comparative manner

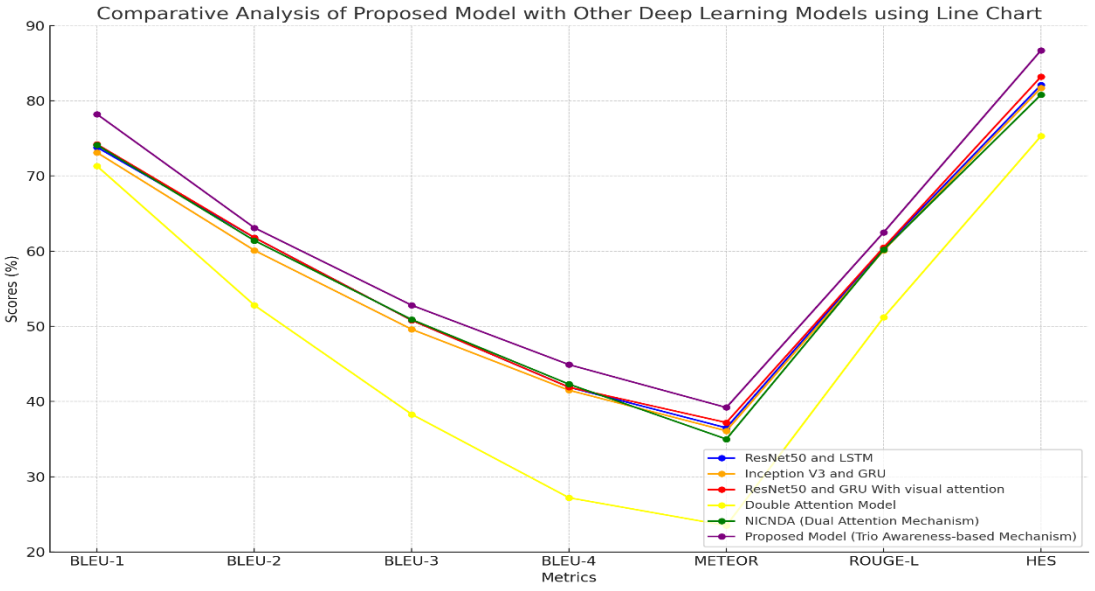

Figure 3 Analysis of Various Models in a comparative manner using line graph

Figure 4 Image caption creation utilising the suggested model

8. Conclusion and Future Work

This research paper presents a framework with a visually enhanced encoder and a semantically enhanced decoder. The encoder generates key region-based features and transfers them to the decoder, which uses GloVe embedding for semantic purposes. The proposed framework generates syntactically and semantically strong captions, outperforming rival frameworks in terms of BLEU scores. In the suggested paradigm, BLEU scores and other evaluation metrics like METEOR, ROUGE-L, and Human Evaluation Score (HES) are significantly higher. Future studies will emphasize using additional attention mechanisms and diverse datasets to cover a broader range of image captioning tasks. This research highlights several open research challenges and literature review insights. The task of image captioning heavily depends on the dataset size, suggesting that training models with larger datasets could improve model quality. Real-life usable devices, such as those converting captured images into text and utilizing sound for visually impaired individuals, could be developed. There is a notable lack of work using unsupervised datasets for image captioning, which holds potential for effective results. Future directions include developing trio attention-based models with higher accuracy and fewer errors.

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Data Availability Statement: The datasets used for the experimentation was taken from Kaggle repository (https://www.kaggle.com/datasets/adityajn105/flicker8k).

Research Involving Human and /or Animals: Not Applicable

Informed Consent: Not Applicable

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