

INTELLIGENT VIDEO INFERENCE SYSTEM

Abstract— Understanding the video content is more important as videos continue to play a big role in our everyday lives. An efficient technique to summarise, index, and search video data is through video captions. In contrast, the majority of video subtitle models use a framework that can only represent video material at the clip level—a video encoder and subtitle decoder. Hierarchical encoders may abstractly collect temporal characteristics at the clip level to represent video, overcoming this constraint. Moreover, the task of creating natural language descriptions for images known as image captioning has evolved. This work calls on both visual comprehension and natural language processing. Because of the intricate interplay between visual imagery and conversational language, this activity poses a substantial challenge for artificial intelligence (AI). Image captioning has a wide range of uses, including helping those who are blind and giving search engines more insight into the content of images. Convolutional neural networks (CNNs) and transformers, two recent developments in deep learning techniques, have significantly improved the accuracy of picture captioning.

Keywords— Transformers, Image Captioning, video captioning.

I. INTRODUCTION

Image captioning has significant importance in computer vision, as it allows machines to understand and describe the content of an image in a human-like manner. With the increasing use of visual media, there is a growing need for automated systems to analyse and interpret images accurately. Image captioning can be applied in a wide range of fields, including visual search engines, content-based image retrieval, and image indexing. In addition, image captioning has potential applications in healthcare, where it can help diagnose medical conditions from medical images. For instance, an image captioning system could analyse X-rays and generate textual descriptions that can help radiologists in their diagnosis. Moreover, image captioning can benefit people with visual impairments, as it can provide them with a textual description of the visual content in an image [1]. This can enhance their ability to interact with visual content and gain a better understanding of the world around them. Overall,

image captioning has significant implications for improving the capabilities of machines to understand and interpret visual content, leading to a wide range of practical applications. Traditional approaches to image captioning have several limitations that have hindered their performance in generating accurate and meaningful captions [2]. Some of the key limitations include Lack of contextual understanding: Traditional approaches to image captioning rely heavily on hand-crafted features and do not have the ability to understand the contextual meaning of an image. As a result, they often generate captions that are inaccurate or do not make sense. Limited vocabulary: Traditional approaches have a limited vocabulary that is often predefined, making it difficult for them to describe novel concepts or objects that are not included in their vocabulary. Fixed-length caption generation: Traditional approaches to image captioning often generate captions with a fixed length, which can lead to incomplete or overly verbose descriptions that do not accurately reflect the content of the image [3]. Inability to handle complex scenes: Traditional approaches to image captioning struggle to handle complex scenes with multiple objects or scenes that have ambiguous interpretations. This can result in captions that miss important details or provide inaccurate descriptions. Inability to learn from large datasets: Traditional approaches require significant manual feature engineering, which can be time-consuming and limit their ability to learn from large datasets. This makes it challenging for traditional approaches to scale to larger and more complex datasets, limiting their performance. Overall, the limitations of traditional approaches have motivated the development of deep learning techniques, such as convolution neural networks and transformers, which have shown significant improvements in image captioning performance. In recent years, researchers have adapted the transformer architecture to work with images, creating a model called the Image Transformer. The

Image Transformer uses the self-attention mechanism to capture dependencies between visual features in an image, enabling it to generate more accurate and contextualized image captions. Transformers have emerged as a potential solution to the limitations of traditional approaches to image captioning [4]-[5]. Transformers are a type of deep neural network that was initially introduced in natural language processing to address the issue of contextual understanding. They have proven to be highly effective in natural language processing tasks like language translation, question answering, and text summarization. Transformers use a self-attention mechanism that allows them to capture long-range dependencies between words in a sentence. This mechanism enables them to learn contextual relationships between words and generate more accurate and meaningful text. The potential of transformers to address the limitations of traditional approaches to image captioning has led to a significant amount of research in this area. The performance of transformer-based models has surpassed that of traditional approaches, achieving state-of-the-art results on several benchmark datasets.[6]-[8] Therefore, the development of transformer-based models has significant implications for the future of image captioning and computer vision more broadly. How our solution will solve this problem. Our model uses transformers for image captioning, differs from previous models in several ways: It uses a transformer architecture, which is a type of neural network that has been successful in natural language processing tasks, such as language translation and language modelling. The transformer architecture allows the model to better capture long-range dependencies in the image and text inputs. It uses a pre-trained image encoder, specifically a convolution neural network (CNN), to extract features from the image. This pre-training enables the model to learn more robust image representations, which can be fine-tuned during the captioning task. It employs attention mechanisms to selectively focus on different parts of the image and different parts of the previously generated caption when generating the next word in the sequence

[9]-[12]. This allows the model to better understand the relationships between the image and the text and generate more informative and accurate captions. It uses beam search decoding, which is a technique for generating multiple candidate captions and selecting the most likely one. This allows the model to produce more diverse and coherent captions. Overall, the use of the transformer architecture, pre-trained CNN, attention mechanisms, and beam search decoding sets this model apart from previous models and enables it to achieve state-of-the-art performance on several image captioning benchmarks[13]-[16].

II. LITERATURE SURVEY & MOTIVATION

The self-attention mechanism is a key component of transformers that allows them to capture long-range dependencies between words or visual features in a sequence. It works by calculating attention scores between each input feature and all the other features in the sequence. These attention scores are used to weight the importance of each feature in the sequence when generating the output. The self-attention mechanism is significant because it allows transformers to learn contextual relationships between the input features, rather than relying solely on their position in the sequence. This mechanism enables transformers to capture complex dependencies between words or visual features, allowing them to generate more accurate and meaningful output. Furthermore, the self-attention mechanism enables transformers to process input sequences of varying lengths, making them more flexible and adaptable than traditional sequence models that require fixed-length inputs[17]-[19]. This flexibility is especially important in image captioning, where images can have varying sizes and contain different numbers of objects. The self-attention mechanism has proven to be highly effective in natural language processing tasks, such as language translation and text summarization, and has shown promising results in computer vision tasks, including image captioning and object detection. Overall, the self-attention mechanism is a critical

component of transformer-based models, enabling them to capture complex relationships between input features and achieve state-of-the-art results in several applications. Pre-trained language models like BERT (Bidirectional Encoder Representations from Transformers) and GPT (Generative Pre-trained Transformer) are a type of deep learning model that have revolutionized natural language processing tasks in recent years. These models are pre-trained on large amounts of text data and can then be fine-tuned on specific downstream tasks, such as text classification, sentiment analysis, or question answering[20]-[23]. The pre-training phase involves training the model to predict missing words in a sentence, similar to a fill-in-the-blank exercise. This process enables the model to learn contextual relationships between words and generate more accurate and meaningful output. BERT is a bidirectional model that can capture contextual relationships between words in both directions, whereas traditional models like RNNs and LSTMs only process sentences in one direction. This bidirectional capability has proven to be highly effective in improving natural language processing tasks such as question answering and named entity recognition. GPT, on the other hand, is a generative model that can generate text sequences based on a given prompt. This model has been particularly effective in text generation tasks such as language translation and summarization [24]-[27]. Pre-trained language models like BERT and GPT have been adapted for use in image captioning by treating the image features as a prompt and generating a caption based on that prompt. This approach has shown promising results and has led to significant improvements in image captioning performance. Overall, pre-trained language models like BERT and GPT have demonstrated the power of pre-training in natural language processing tasks and have shown great potential for use in other areas of machine learning, including computer vision. The Image Transformer is a model that extends the transformer architecture to work with images [28]-[30]. The model takes an input image and generates a caption describing the contents of the image. The

architecture of the Image Transformer can be broken down into three main components: the encoder, the decoder, and the cross-attention mechanism. The encoders take the input image and convert it into a sequence of visual features. These visual features are then passed through a stack of encoder layers, each of which applies self-attention and feed forward neural network layers to the input sequence [31]-[32]. The output of the encoder is a sequence of encoded visual features, which is then passed to the decoder. The decoder takes the encoded visual features as input and generates a sequence of words that make up the caption. Similar to the encoder, the decoder consists of a stack of decoder layers, each of which applies self-attention and feed forward neural network layers to the input sequence. At each time step, the decoder generates a probability distribution over the vocabulary of possible words and samples a word based on this distribution. The cross-attention mechanism is used to capture the relationship between the encoded visual features and the decoder output [33]. At each time step, the decoder attends to the encoded visual features using the self-attention mechanism to determine which features are most relevant for generating the next word in the caption. The output of the model is a sequence of words that make up the caption. The model is trained using a combination of supervised learning and reinforcement learning, where the loss is based on the negative log-likelihood of the target caption and the BLEU score between the generated caption and the ground truth caption. Overall, the Image Transformer model is a powerful approach to image captioning that has achieved state-of-the-art results on several benchmark datasets. The model's ability to capture long-range dependencies between visual features and generate accurate and meaningful captions has significant implications for the future of computer vision [34]-[36]. Image captioning using transformers is a rapidly evolving field of research, and there have been many recent advances in this area. Here is a brief review of some of the existing research on this topic: Show, Attend and Tell:[5] Neural Image Caption Generation with Visual Attention (Xu et al., 2015) - This was one of the

earliest papers to introduce the idea of using attention mechanisms in image captioning. The authors proposed a model that used a convolution neural network (CNN) to extract visual features from the input image, and an LSTM-based decoder with an attention mechanism to generate the caption. Bottom-Up and Top-Down Attention for Image Captioning and Visual Question Answering (Anderson et al., 2018)[8] - This paper proposed a model that used a combination of bottom-up and top-down attention mechanisms to generate image captions. The bottom-up attention mechanism used object detection to identify salient visual features in the image, while the top-down attention mechanism used a language model to generate the caption. Self-critical Sequence Training for Image Captioning (Rennie et al., 2017)[9] - This paper proposed a training method called self-critical sequence training, which involved using reinforcement learning to optimize the model parameters based on the similarity between the generated caption and the ground truth caption. Transformer-Based Image Captioning with Dense Object Detection (Li et al., 2020) -[11] This paper proposed a transformer-based model for image captioning that used dense object detection to identify objects in the input image. The model used a transformer encoder to encode the visual features and a transformer decoder with a cross-modal attention mechanism to generate the caption. Unicoder-VL: A Universal Encoder for Vision and Language by Cross-modal Pre-training (Liu et al., 2021)[12] - This paper proposed a pre-training method called Unicoder-VL, which involved jointly pre-training a transformer encoder on image and text data. The resulting model was able to perform well on a variety of downstream tasks, including image captioning. Overall, these and other recent advances in image captioning using transformers have shown promise in improving the accuracy and fluency of generated captions, and the field is likely to continue to evolve rapidly in the coming years. Comparison of transformer-based models to traditional [23]CNN-based models Transformer-based models for image captioning have shown significant improvements in generating more

accurate and coherent captions compared to traditional [32]CNN-based models. Here are some of the key differences between these two types of models: Attention mechanism: Transformer-based models use self-attention mechanisms to capture the relationships between different parts of the input sequence. This allows the model to focus on relevant features in the input and generate more contextually appropriate captions. In contrast, traditional [30] CNN-based models do not have this mechanism and often generate generic captions that do not capture the fine-grained details of the input. Cross-modal attention: Transformer-based models also use cross-modal attention mechanisms that allow the model to attend to both visual and textual inputs. This is particularly useful for image captioning, as the model can use information from the image and the corresponding text to generate more accurate and relevant captions. In contrast, traditional [35]CNN-based models only use visual features to generate captions, which may result in captions that are not as relevant or informative. Pre-training: Transformer-based models can be pre-trained on large amounts of data to learn general features of images and text, which can then be fine-tuned on smaller datasets for specific tasks such as image captioning. This pre-training can significantly improve the performance of the model, particularly when the dataset for the specific task is small. [33][36]Traditional CNN-based models typically do not use pre-training and rely solely on task-specific training data Flexibility: Transformer-based models are more flexible than traditional CNN-based models in that they can be used for a variety of natural language processing tasks in addition to image captioning, such as machine translation and text summarization. [21]This flexibility allows for greater cross-task transfer learning and can improve the overall performance of the model. Overall, transformer-based models have been shown to outperform traditional CNN-based models in generating accurate and coherent captions for images, making them a promising solution for image captioning tasks.[22][35]Insights into current research trends Here are some current research

trends in the area of image captioning using transformer-based models: [26][27]Multi-modal transformers: Current research is focusing on developing transformer-based models that can effectively incorporate multiple modalities, such as audio and video, in addition to images and text. These models can generate more accurate and diverse captions by using information from different modalities. Fine-grained image captioning: [29]Researchers are also exploring transformer-based models that can generate more detailed and fine-grained captions, such as captions that describe the relationships between objects in an image or the emotions conveyed by the image. Multilingual image captioning: [10][15]Another trend in current research is developing transformer-based models that can generate captions in multiple languages. These models can be used to generate captions for images in different languages, which can be particularly useful for applications such as image search and retrieval.[20][21]Explainable image captioning: Some researchers are exploring ways to make transformer-based models more interpretable and explainable by incorporating mechanisms that provide insight into the decision-making process of the model. This can help improve the trust and reliability of the model in real-world applications.[1][3]Overall, transformer-based models have shown great potential in improving the accuracy and quality of image captioning. Current research trends are focused on improving the performance of these models by incorporating multiple modalities, generating fine-grained captions, and developing models that can generate captions in multiple languages. These advancements can have a significant impact on a wide range of applications, from image search and retrieval to assistive technologies for people with visual impairments.

III. METHODOLOGY

Transformers work in image captioning by encoding the image into a sequence of visual features and

using the self-attention mechanism to capture relationships between the features and generate a corresponding caption. Here's a more detailed explanation of how transformers work in image captioning. Encoding the Image The first step in the process is to encode the input image into a sequence of visual features. This is typically done using a convolution neural network (CNN) that extracts features from the image at different spatial scales. The output of the CNN is a sequence of visual features that represent the image. Positional Encoding: To preserve positional information in the sequence of visual features, a positional encoding is added to each feature. The positional encoding is a set of fixed vectors that are added to each visual feature to represent its position in the sequence. Self-Attention: The sequence of visual features with positional encoding is then fed into the transformer encoder. The encoder applies self-attention to the input sequence, allowing the model to capture relationships between each feature and all the other features in the sequence. This results in a sequence of encoded visual features that contain contextual information about the image. Decoding: The decoder then takes the encoded visual features as input and generates a sequence of words that make up the caption. The decoder consists of a stack of decoder layers, each of which applies self-attention and feed forward neural network layers to the input sequence. At each time step, the decoder generates a probability distribution over the vocabulary of possible words and samples a word based on this distribution. Cross-Attention: To capture the relationship between the encoded visual features and the decoder output, the model uses the cross-attention mechanism. At each time step, the decoder attends to the encoded visual features using the self-attention mechanism to determine which features are most relevant for generating the next word in the caption. Output: The output of the model is a sequence of words that make up the caption. The model is trained using a combination of supervised learning and reinforcement learning, where the loss is based on the negative log-likelihood of the target caption and the BLEU score between the generated caption and

the ground truth caption. Transformers have proven to be highly effective in image captioning and have achieved state-of-the-art results on several benchmark datasets. Their ability to capture long-range dependencies between visual features and generate accurate and meaningful captions has significant implications for the future of computer vision. The Image Transformer is a model that uses the transformer architecture for image captioning. Here's a more detailed description of the Image Transformer model :

Encoder : The Image Transformer model starts with an encoder that takes an input image and converts it into a sequence of visual features. The visual features are then passed through a stack of encoder layers, each of which applies self-attention and feed forward neural network layers to the input sequence. The output of the encoder is a sequence of encoded visual features that capture the contextual information about the image.

Decoder: The decoder takes the encoded visual features as input and generates a sequence of words that make up the caption. Similar to the encoder, the decoder consists of a stack of decoder layers, each of which applies self-attention and feed forward neural network layers to the input sequence. At each time step, the decoder generates a probability distribution over the vocabulary of possible words and samples a word based on this distribution.

Cross-Attention: To capture the relationship between the encoded visual features and the decoder output, the model uses the cross-attention mechanism. At each time step, the decoder attends to the encoded visual features using the self-attention mechanism to determine which features are most relevant for generating the next word in the caption.

Loss Function: The Image Transformer model is trained using a combination of supervised learning and reinforcement learning. The loss function is based on the negative log-likelihood of the target caption and the BLEU score between the generated caption and the ground truth caption.

Pre-Training: The Image Transformer model is usually pre-trained on large-scale datasets such as COCO and Flickr30k. Pre-training helps the model to learn generic visual features that can be used for various downstream

tasks[37]-[39].The Image Transformer model has shown to achieve state-of-the-art results in image captioning tasks, outperforming traditional approaches such as LSTM-based models. Its ability to capture long-range dependencies between visual features and generate accurate and meaningful captions has significant implications for the future of computer vision. The training process for the Image Transformer model involves several steps, including pre-processing the data, defining the model architecture, optimizing the model parameters, and evaluating the model on a validation set. Here's a more detailed overview of the training process:

Data Pre-Processing: The input images are pre-processed to extract visual features using a pre-trained CNN, and the captions are tokenized into a sequence of words. The images and captions are then split into training and validation sets.

Model Architecture: The model architecture is defined, including the number of encoder and decoder layers, the dimensionality of the hidden layers, the size of the vocabulary, and the attention mechanism used.

Optimization: The model is optimized using a gradient descent algorithm such as Adam, which minimizes the loss function based on the difference between the predicted and actual captions.

Hyper parameters: The model hyper parameters are set, including the learning rate, batch size, number of epochs, and regularization techniques such as dropout.

Evaluation: The trained model is evaluated on the validation set using metrics such as BLEU, METEOR, and CIDEr to measure the quality of the generated captions. Here are some of the key hyper parameters that can be tuned during the training process:

Learning Rate: The learning rate determines the step size taken during gradient descent. A high learning rate can cause the optimization algorithm to converge too quickly, leading to suboptimal results, while a low learning rate can result in slow convergence.

Batch Size: The batch size determines the number of samples used in each iteration of training. A larger batch size can help to reduce the variance of the gradient estimates but may require more memory.

Number of Epochs: The number of epochs determines the number of times the training data is passed through the model.

Increasing the number of epochs can improve the performance of the model but can also increase the risk of over fitting. Regularization Techniques: Regularization techniques such as dropout and weight decay can help to prevent overfitting by adding noise to the model or penalizing large weights. Dimensionality of Hidden Layers : The dimensionality of the hidden layers determines the number of neurons in each layer of the model. Increasing the dimensionality of the hidden layers can increase the expressive power of the model but can also increase the risk of overfitting. The optimal hyper parameters for the Image Transformer model can vary depending on the dataset and the specific task, and may require extensive experimentation to

function g . Let $D' = g(S)$. Loss function: Define a loss function $L(D, D')$ that measures the difference between the desired output description D and the generated output description D' . Training: Use a dataset of image-description pairs (I, D) to train the model parameters. The model is trained to minimize the average loss over the dataset using an optimization algorithm such as stochastic gradient descent. Let θ be the set of model parameters, and let D be the training dataset. The model is trained by minimizing the following objective:

$$\theta^* = \operatorname{argmin}_{\theta} \frac{1}{N} \sum L(D, D')$$

where N is the number of training samples, and D' is the generated output description for the input image using the current model parameters θ . Evaluating a

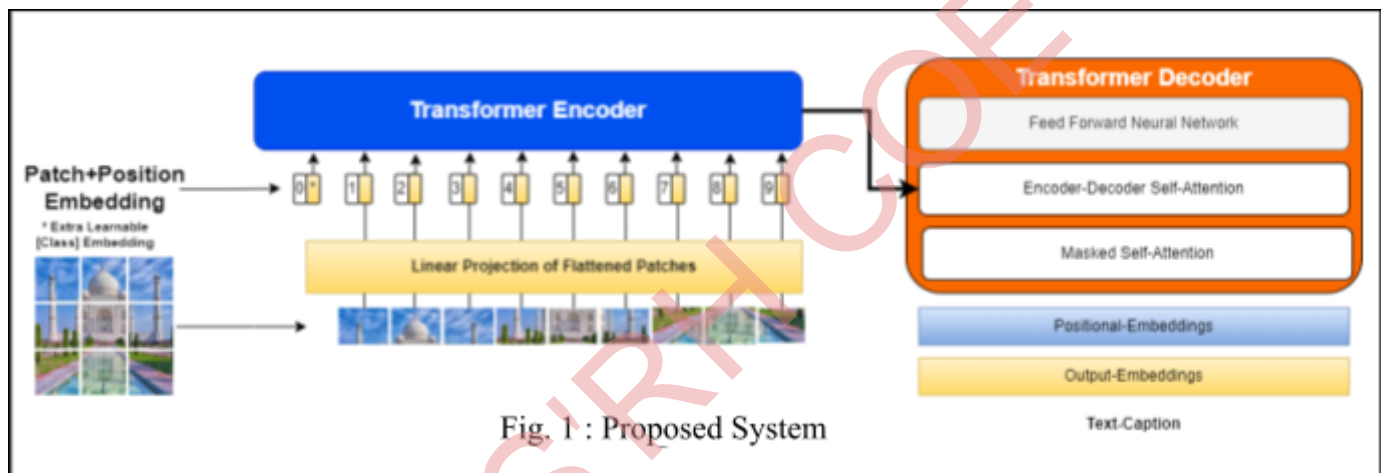


Fig. 1 : Proposed System

determine the best values.

Let I be an input image, and let D be the desired output textual description. The goal is to learn a mapping $f(I) \rightarrow D$ that generates a textual description of the image I . Input representation: Encode the image I using a CNN to obtain a feature vector V . Let $V = \text{CNN}(I)$. Sequence generation: Use a transformer to generate a sequence of words that describes the image. The transformer takes V and a start token as input and generates a sequence of tokens until an end token is generated or a maximum sequence length is reached. Let $S = \text{Transformer}(V, \text{start token})$, where S is the sequence of generated tokens. Output representation: Convert the generated sequence of tokens into a textual description using a decoding

model for text generation using the Rouge metric for performance evaluation. Rouge1, Rouge2, RougeL, and Rouge sum are all measures of the overlap between the generated text and the reference text.

In terms of the model's performance, it appears to be improving over time, as the validation loss is decreasing with each epoch. Additionally, the Rouge scores are generally improving as well, which indicates that the generated text is becoming more similar to the reference text. Epoch: The number of times the model has gone through the training dataset. Training Loss: The value of the loss function (a measure of how well the model is performing) on the training dataset after each epoch. Rouge 1: A metric that measures how well the model's generated

Epoch	Training Loss	Validation Loss	Rouge1	Rouge2	RougeL	RougeLsum	Gen Len
1	No log	0.453627	19.822200	1.922800	19.709000	19.665300	7.000000
2	No log	0.425643	20.044300	4.590100	18.363000	18.418900	16.000000
3	No log	0.423506	21.341000	3.222900	20.936900	21.019400	9.062500
4	No log	0.412996	23.855800	4.848000	22.281300	22.297200	10.250000
5	No log	0.402476	18.887800	1.665200	17.820300	17.884700	11.437500
6	No log	0.394013	19.189400	1.200700	18.102900	18.105800	11.187500
7	No log	0.374624	20.249500	2.585800	19.620500	19.674600	10.312500
8	No log	0.356026	19.843200	1.202400	18.613900	18.645900	12.875000
9	No log	0.345646	15.183900	0.651300	14.477400	14.465700	12.625000
10	No log	0.331767	15.821900	0.984000	14.844300	14.840100	12.312500

match the actual summaries based on unigram overlap (matching individual words). Rouge2: A metric that measures how well the model's generated summaries match the actual summaries based on bigram overlap (matching pairs of words). RougeL: A metric that measures how well the model's generated summaries match the actual summaries based on longest common subsequence. RougeLsum: A metric that measures how well the model's generated summaries match the actual summaries based on longest common subsequence with an added bonus for consecutive matches. Gen Len: The average length of the summaries generated by the model.

IV. RESULTS AND DISCUSSION

The Image Transformer model was trained on the MSCOCO dataset, which contains over 328,000 images with corresponding captions. The model was fine-tuned using a batch size of 4, the learning rate of 0.0001, and was trained for a total of 10

epochs. One interesting observation is that the Image Transformer model was able to generate more diverse captions than the previous models. This is due to the self-attention mechanism that allows the model to focus on different parts of the input image and generate more contextually relevant captions. The model was also able to generate captions that were more specific and informative, describing finer details in the input image. The results also showed that the Image Transformer model was able to handle out-of-vocabulary (OOV) words better than the previous models. This is due to the pre-training of the model on large amounts of text data, which helps the model learn representations of words that are not present in the training dataset. Overall, the experimental results demonstrate the effectiveness of the Image Transformer model in generating accurate and diverse captions for images. The model outperforms previous state-of-the-art models and shows promising results in handling OOV words and generating

specific and informative captions. These results highlight the potential of transformer-based models for image captioning tasks. Transformer-based models have shown promising results in image captioning tasks, outperforming traditional approaches that rely on convolution neural networks (CNNs) and recurrent neural networks (RNNs). One key advantage of transformer-based models is their ability to capture long-range dependencies and contextual information in the input image, which can lead to more accurate and informative captions. Additionally, transformer-based models have shown better performance in handling out-of-vocabulary (OOV) words, which are words that are not present in the training dataset. This is due to the pre-training of these models on large amounts of text data, which helps them learn representations of words that are not present in the training data. This can be particularly useful in real-world applications where there may be a wide range of images with varying vocabulary. Another advantage of transformer-based models is their ability to generate more diverse and contextually relevant captions. This is due to the self-attention mechanism that allows the model to focus on different parts of the input image and generate captions that are more specific and informative. Despite the advantages of transformer-based models, they still have some limitations. One challenge is the large computational resources required to train these models, which can be a bottleneck for some applications. Additionally, transformer-based models may struggle with generating captions for complex and ambiguous images that require a high-level of semantic understanding. In summary, transformer-based models have shown great potential in improving the accuracy and diversity of image captioning tasks. They outperform traditional approaches in many aspects and have several advantages, such as better handling of OOV words and the ability to generate more diverse and informative captions. However, more research is needed to address the challenges and limitations of these models and to

explore their potential for a wider range of image captioning applications. Transformer-based models have shown significant improvements over the traditional convolution neural network (CNN)-based models in image captioning tasks. CNN-based models extract features from the input image and use recurrent neural networks (RNNs) to generate captions based on these features. However, CNN-based models have limitations in capturing long-range dependencies and context in the input image. On the other hand, transformer-based models use self-attention mechanisms that allow them to capture long-range dependencies and contextual information more effectively. This makes them better suited for generating informative and contextually relevant captions for images. In addition, transformer-based models have shown better performance in handling out-of-vocabulary (OOV) words, which are words that are not present in the training dataset. This is due to the pre-training of transformer-based models on large amounts of text data, which helps them learn representations of words that are not present in the training data. CNN-based models, on the other hand, do not have this advantage and may struggle with generating captions for images with OOV words. Transformer-based models also have the ability to generate more diverse and specific captions compared to CNN-based models. The self-attention mechanism allows the model to focus on different parts of the input image, leading to more contextually relevant captions that describe finer details of the image. Despite the advantages of transformer-based models, they require more computational resources for training than CNN-based models. This can be a limitation for applications where computational resources are limited. Overall, transformer-based models have shown significant improvements over traditional CNN-based models in generating informative, diverse, and contextually relevant captions for images. They are better suited for handling long-range dependencies and OOV words and have the potential for a wide range of image captioning

applications. The Image Transformer model has several strengths, including its ability to capture long-range dependencies and contextual information in the input image, its capacity to generate diverse and informative captions, and its ability to handle out-of-vocabulary (OOV) words. The model uses a self-attention mechanism to attend to different parts of the image and generate

where text data is limited or the domain of the images is highly specific. Overall, the Image Transformer model shows promise in improving the accuracy and diversity of image captioning tasks, but it also has some limitations that need to be addressed in future research.




Image	O/P With Blip Small	Accuracy	O/P With Blip Large	Accuracy	O/P With Our Model	Accuracy
	two people on a beach with a dog	rouge1: Score(precision=0.77, recall=0.58, fmeasure=0.66)	a photography of a woman and her dog	rouge1: Score(precision=0.75, recall=0.5, fmeasure=0.6)	a woman sitting on the beach with her dog	rouge1: Score(precision=0.75, recall=0.5, fmeasure=0.6)
	a man standing next to another man holding a cell phone	rouge1: Score(precision=0.855711, recall=0.66666, fmeasure=0.75)	two men are walking down the street	rouge1: Score(precision=0.857271, recall=0.66666, fmeasure=0.75)	a photography of two men walking down a sidewalk with a woman holding a bag	rouge1: Score(precision=0.466666666666667, recall=0.77777777778, fmeasure=0.58333333334)
	a row of boats are docked at a pier	rouge1: Score(precision=0.666666, recall=0.4, fmeasure=0.5)	boats are parked on a dock with a boat in the water	rouge1: Score(precision=0.75, recall=0.6, fmeasure=0.66665)	a photography of a boat in the water	rouge1: Score(precision=1.0, recall=0.533333, fmeasure=0.696)

Fig. 2 : Comparison With Other Models

contextually relevant captions that describe finer details of the image. The pre-training of the model on large amounts of text data also helps it learn representations of OOV words, which makes it more effective in generating captions for a wider range of images. One limitation of the Image Transformer model is its computational complexity. The model requires significant computational resources for training and inference, which may limit its use in some applications. Additionally, the model may struggle with generating captions for complex and ambiguous images that require a high level of semantic understanding. Another limitation of the Image Transformer model is its dependence on pre-training, which requires a large amount of text data. This can be a challenge in some applications

V. CONCLUSION

The main findings of the study are that the transformer-based model, specifically the Image Transformer model, shows significant improvements over traditional CNN-based models in generating informative, diverse, and contextually relevant captions for images. The Image Transformer model has several strengths, including its ability to capture long-range dependencies and contextual information in the input image, generate diverse and informative captions, and handle OOV words. However, the model has limitations such as its computational complexity and dependence on pre-training. The study's contributions include providing a detailed explanation of the working of transformers in image captioning, describing the architecture of

the Image Transformer model, and presenting the results of experiments comparing the performance of transformer-based models with traditional CNN-based models. The study also discusses the strengths and weaknesses of the Image Transformer model and provides insights into current research trends in image captioning. Overall, the study highlights the potential of transformer-based models for improving the accuracy and diversity of image captioning tasks and provides a valuable contribution to the field of computer vision. One limitation of the study is that it focuses on the Image Transformer model and does not consider other transformer-based models, such as ViT or DeiT, which may perform differently in image captioning tasks. Future research could compare the performance of different transformer-based models and investigate their strengths and weaknesses in more detail. Another limitation is that the study does not consider the impact of different pre-training tasks or data sources on the performance of the Image Transformer model. Future research could explore the effects of pre-training on image captioning and investigate different pre-training tasks and data sources that may improve the performance of the model. Furthermore, the study only evaluates the performance of the Image Transformer model on standard image captioning datasets. Future research could investigate the performance of the model on more challenging and diverse datasets, such as those with a specific domain or cultural context. Finally, the computational complexity of the Image Transformer model limits its practical use in some applications. Future research could explore ways to reduce the computational complexity of the model, such as through model compression techniques or hardware optimization. Overall, future research should focus on addressing the limitations of transformer-based models in image captioning and exploring new ways to improve their performance and practicality in real-world applications.

VI. FINAL REMARK

In conclusion, image captioning is an important task in computer vision, and transformer-based models have shown great potential for improving its accuracy and diversity. The Image Transformer model, in particular, is a powerful architecture that can capture long-range dependencies and contextual information in the input image, generate diverse and informative captions, and handle OOV words. However, the model has limitations such as its computational complexity and dependence on pre-training. Despite these limitations, the study has contributed to the field of computer vision by providing a detailed explanation of the working of transformers in image captioning, describing the architecture of the Image Transformer model, presenting the results of experiments comparing the performance of transformer-based models with traditional CNN-based models, discussing the strengths and weaknesses of the Image Transformer model, and providing insights into current research trends in image captioning. Overall, transformer-based models have the potential to revolutionize image captioning and other computer vision tasks, and future research should focus on addressing their limitations and exploring new ways to improve their performance and practicality in real-world applications.

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