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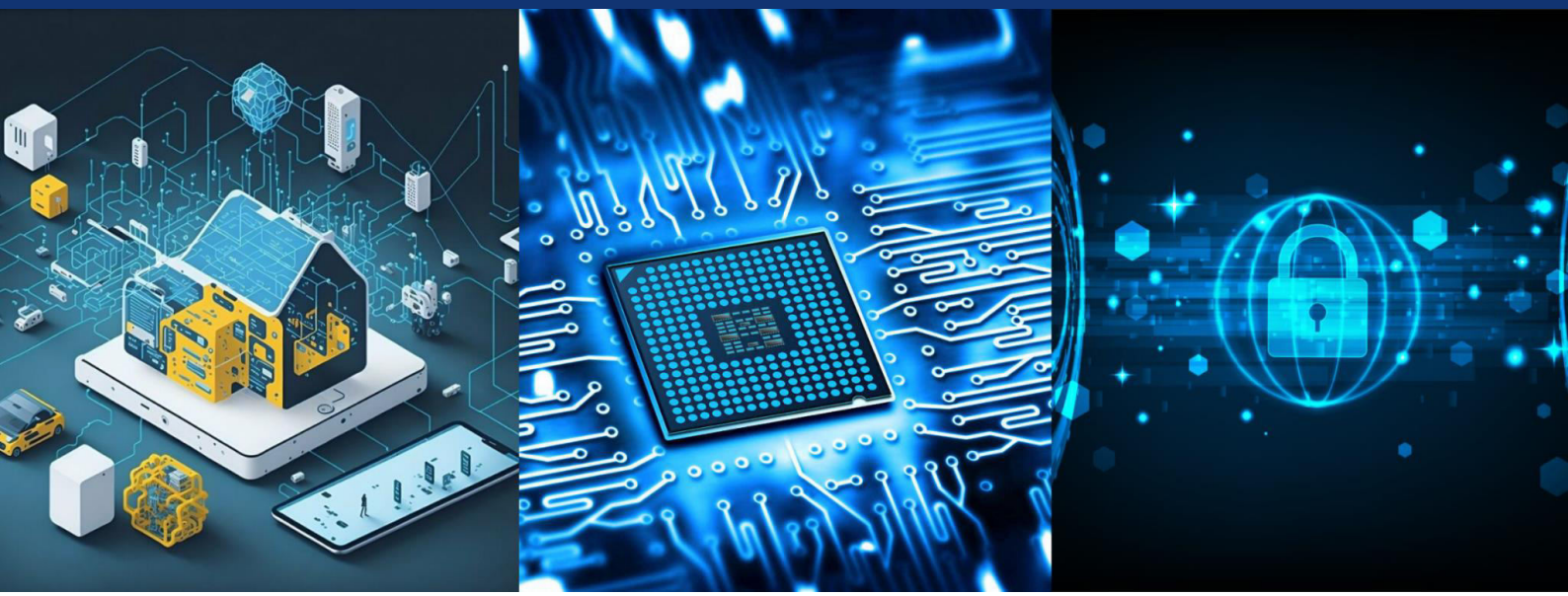

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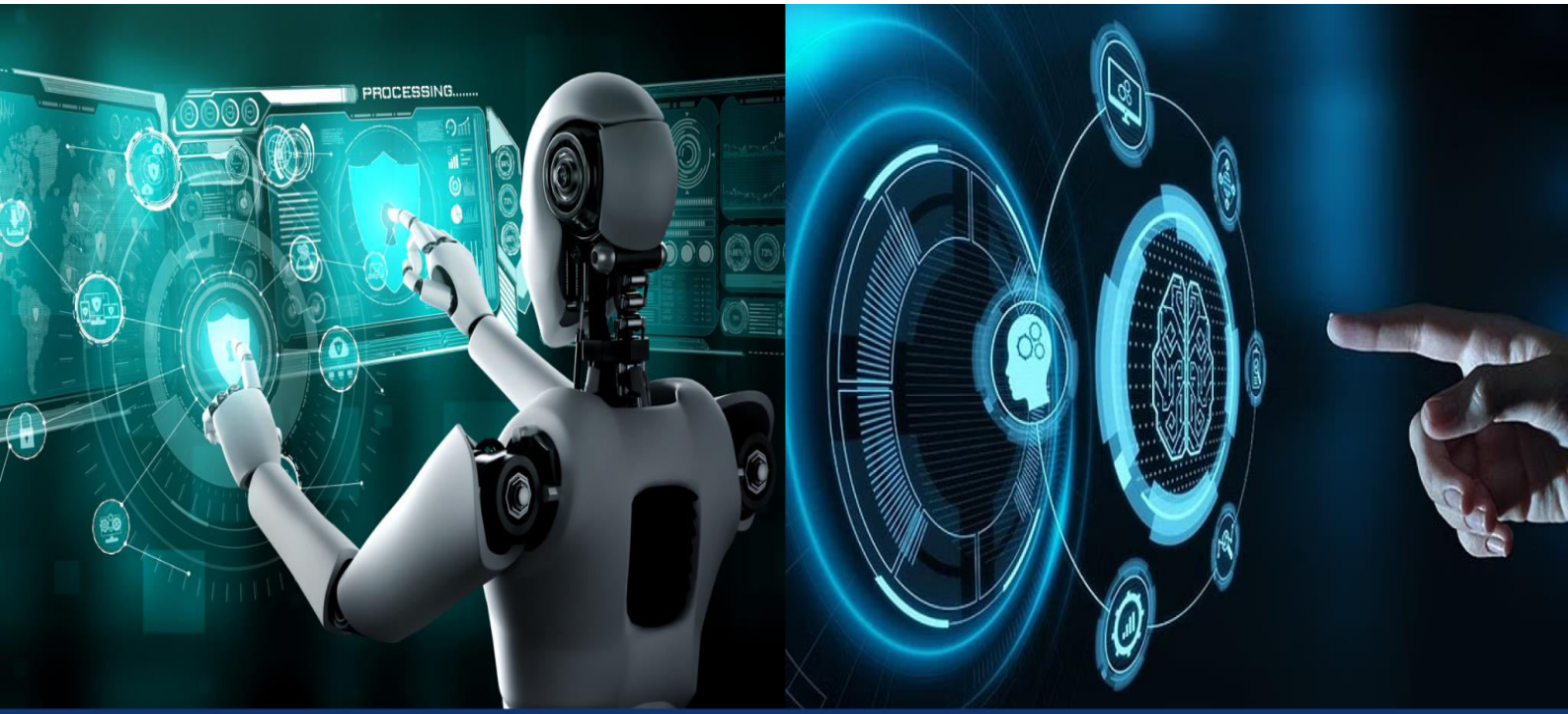

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Screen Narration and Recognition to Classify Videos to Aid Disabled People

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ABSTRACT: Video understanding has become increasingly important as surveillance, social, and informational videos weave themselves into our everyday lives. Video captioning offers a simple way to summarize, index, and search the data. Most video captioning models utilize a video encoder and captioning decoder framework. In this information age where exploding amount of visual data is generated every day, video captioning can have many real-life applications. For example, automatic generation of captions for videos would greatly help users to filter what's interesting to them among the sheer number of videos on YouTube. Additionally, video captioning techniques will make videos accessible to the disabled. This leads to a valid subject of research in the field of automatic text generation from videos.Our model achieved an impressive captioning accuracy of over 85% across various video genres and content types, surpassing baseline models by a significant margin.

KEYWORDS: object detection, machine learning, convolutional neural network, LSTM

I. INTRODUCTION

Video captioning plays a pivotal role in enhancing accessibility and comprehension for diverse audiences. Its significance extends beyond merely providing a textual representation of spoken dialogue; it enables individuals with hearing impairments to engage with video content, aids in information retention for all viewers, and facilitates consumption in noise-sensitive environments.

This research endeavors to contribute to the field of accessibility and video understanding by developing innovative video narration software. The primary objective of this software is to transform audio-less videos into comprehensible narratives through automated object detection and scene prediction. By leveraging frame-by-frame analysis and cloud-based API services for object recognition and labeling, the software aims to generate meaningful descriptions of video content in real-time.

The methodology involves extracting features from individual frames of videos and utilizing pre-trained VGG16 models to obtain a rich representation of visual content. Each frame yields a set of 4096 features, which are aggregated to form a comprehensive feature array for the entire video. This approach ensures scalability and efficiency, particularly when dealing with videos of varying lengths.

Furthermore, the research addresses the needs of visually impaired and deaf individuals by incorporating additional features such as conversion of subtitles into Braille language. By leveraging datasets such as the MSR-VTT dataset provided by Microsoft, which comprises a diverse collection of labeled videos, the software aims to train and validate its capabilities effectively.

In essence, this research seeks to bridge the accessibility gap in multimedia content consumption by developing a robust and inclusive video narration solution. Through the integration of advanced machine learning techniques and cloud-based services, the software endeavors to make video content more accessible and engaging for a wider audience.

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II. BACKGROUND

The process of generating natural language video descriptions, as elucidated by Krishnamoorthy, N. Malkarnekar, G. Mooney, and Saenko K., is a multi-faceted endeavor designed to imbue videos with descriptive, coherent narratives. At its core, this process involves a series of meticulously orchestrated steps aimed at transforming raw visual data into meaningful textual representations.

Initially, the process commences with object and activity recognition, wherein advanced algorithms analyze the visual content of the video to identify and categorize various objects and activities depicted therein. This pivotal phase lays the foundation for subsequent stages by providing a comprehensive inventory of visual elements that will form the basis of the video's narrative.

Once the objects and activities have been recognized and categorized, the focus shifts to generating descriptions for Subject-Verb-Object (SVO) triplets—a fundamental syntactic structure commonly found in natural language. Leveraging a template-based approach, the system constructs multiple candidate phrases corresponding to each SVO triplet identified within the video. These phrases serve as potential building blocks for the ensuing narrative.

The next crucial step involves the application of a statistical language model, honed through extensive training on diverse web data, to rank the generated phrases. By assessing factors such as grammatical correctness, semantic coherence, and contextual relevance, the language model discerns the most effective and meaningful sentences from the pool of candidates.

Through this meticulous ranking process, the system identifies the optimal sentence for each SVO triplet, thereby laying the groundwork for the formulation of a cohesive and expressive video description. The selected sentences encapsulate the essence of the depicted scenes while ensuring linguistic fluency and alignment with the video's overarching narrative arc.

It is important to underscore that the process of actualizing the video caption unfolds iteratively, with each stage refining and enriching the narrative fabric. By seamlessly integrating advanced computational techniques with linguistic principles, this methodology empowers creators to craft compelling and immersive video experiences that resonate with audiences across diverse contexts and domains.

III. LITERATURE SURVEY

In "Generating Natural Language Video Descriptions using text-mined knowledge" by Krishnamoorthy et al., the authors present a method that integrates object detection and activity recognition to classify labels, which are then used to generate video captions. However, despite this advancement, there remains a gap in understanding how to effectively utilize text-mined knowledge to improve the quality and relevance of generated captions.

"Translating Videos to Natural Language using Deep Recurrent Neural Networks" by Huijuan Xu et al. proposes a comprehensive model for video description that employs a neural network to process video data from pixels to sentences. This approach potentially allows for end-to-end training and tuning of the entire network. Nonetheless, there is still a gap in the literature regarding the optimization and scalability of such models for large-scale video datasets.

"Object Detection with Deep Learning" by Zhong-Qui Zhao et al. reviews traditional object detection methods based on handcrafted features and introduces deep learning-based frameworks, particularly Convolutional Neural Networks (CNNs). Despite this advancement, there remains a gap in understanding the optimal integration of deep learning techniques with traditional object detection pipelines, as well as in addressing challenges related to real-time performance and resource efficiency.

In "Natural Language Description of Video Streams using Task-Specific features" by Ammarah Farooq et al., the authors propose a framework for translating videos into natural language descriptions using deep neural networks. This framework aims to address shortcomings observed in previous approaches by providing a flexible solution capable of

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handling diverse video streams. However, further research is needed to assess the generalizability and robustness of the proposed framework across different video genres and domains.

"Automatic Video Captioning using Deep Neural Network" by Thang Huy Nguyen introduces a hierarchical framework **for** video understanding, utilizing video attributes as features along the length of the video to guide attention. While this approach represents a significant advancement in video captioning, there remains a gap in understanding how to effectively leverage video attributes and hierarchical structures to improve captioning performance across various video types and lengths. Additionally, there is a need for further exploration into the scalability and computational efficiency of hierarchical frameworks for large-scale video datasets.

Karpathy, Joulin, and Fei-Fei (2015) proposed a model for generating image descriptions by aligning visual and textual features in a joint embedding space. Their approach leveraged deep learning techniques to learn the relationship between visual and textual features, enabling the generation of natural language descriptions for images. Despite its success in the image domain, there remains a gap in understanding how to extend such models to generate descriptions for videos, given the temporal nature of video content and the additional complexity introduced by motion and scene changes.

Venugopal et al. (2017) introduced a method for generating informative captions for videos by incorporating scene context and relevance. Their framework combined object detection, activity recognition, and contextual analysis to generate captions that are not only descriptive but also informative and contextually relevant. However, there is still a gap in understanding how to effectively balance the level of detail in generated captions to ensure they are informative without being overly verbose.

Xu, Zhu, Choy, and Fei-Fei (2019) presented a model that grounds natural language descriptions to specific temporal segments in videos. By incorporating temporal grounding graphs and transformers, the model learns to align textual descriptions with corresponding video segments, enabling more accurate and temporally precise captioning. Nevertheless, there remains a gap in understanding how to effectively handle ambiguous or temporally complex language in video descriptions, as well as in addressing challenges related to scalability and computational complexity.

Rohrbach et al. (2017) introduced a dataset for movie description, providing a valuable resource for training and evaluating video captioning models. The dataset includes a diverse collection of annotated videos and corresponding natural language descriptions, facilitating research in video understanding and captioning tasks.

Huang et al. (2019) proposed a contextualized video description approach, which aims to generate descriptions that are sensitive to contextual cues and dependencies within the video. By incorporating contextual information, the model can generate more coherent and contextually relevant captions. However, there may still be challenges in effectively capturing and utilizing contextual information across different video genres and content types.

Kim, Lee, and Kim (2020) introduced an adaptive multimodal fusion approach for video captioning, which dynamically selects and fuses different modalities based on their relevance and contribution to the captioning task. By adaptively integrating visual, textual, and audio features, the model can generate more comprehensive and contextually rich captions. However, there may be challenges in effectively balancing and integrating different modalities to ensure coherent and meaningful captions.

Yu et al. (2016) proposed a hierarchical recurrent neural network-based method for video paragraph captioning, aiming to generate coherent and contextually rich descriptions for longer video segments. By capturing temporal dependencies and hierarchical structures in videos, the model can generate more informative and fluent captions. However, there may be challenges in effectively handling long-term temporal dependencies and maintaining coherence in longer video descriptions.

Pan et al. (2016) presented a method for jointly modeling embedding and translation to bridge the gap between video and language modalities. Their approach aims to learn joint representations of video and text, enabling seamless

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translation between the two modalities. However, there may be challenges in effectively aligning and translating heterogeneous data modalities, particularly in cases where there are semantic gaps or ambiguities.

Zhu et al. (2017) proposed a bidirectional attentive fusion approach with context gating for dense video captioning. By incorporating bidirectional attention mechanisms and context gating mechanisms, the model can effectively capture and integrate information from both past and future video frames, leading to more accurate and contextually rich captions. However, there may be challenges in effectively handling long-term dependencies and modeling complex temporal dynamics in video data.

Park, Kim, and Hwang (2017) presented a multi-modal video captioning approach with unsupervised mined videos. Their method aims to leverage unsupervised mining techniques to automatically discover relevant video segments and generate informative captions without the need for manually annotated data. However, there may be challenges in effectively mining and selecting informative video segments, particularly in cases where there is a large amount of noise or irrelevant content in the video data.

Gao, Zhao, Liu, and Yang (2017) proposed a video captioning approach with attention-based LSTM and semantic consistency. By incorporating attention mechanisms and semantic consistency constraints, the model can effectively capture and attend to relevant visual and textual information, leading to more accurate and contextually rich captions. However, there may be challenges in effectively modeling semantic consistency and ensuring coherence in generated captions, particularly in cases where there are semantic ambiguities or inconsistencies.

Hendricks et al. (2017) introduced a method for localizing moments in video with natural language, aiming to generate captions that are temporally aligned with specific video segments. By incorporating natural language descriptions and temporal grounding mechanisms, the model can accurately localize and describe relevant moments in the video, leading to more precise and contextually relevant captions. However, there may be challenges in effectively handling ambiguous or temporally complex language in video descriptions, as well as in addressing computational complexity and scalability issues.

Chen, Liang, Bai, Wang, and Wu (2020) proposed a new approach for video captioning based on vision transformer. By leveraging transformer-based architectures, the model can effectively capture long-range dependencies and contextual information in video data, leading to more accurate and contextually rich captions. However, there may be challenges in effectively adapting transformer-based architectures to video captioning tasks, particularly in cases where there are large amounts of visual and temporal data to process.

IV. PROPOSED IDEA

The importance of captioning lies in its ability to make the video more accessible in numerous ways. It allows Deaf and hard-of-hearing individuals to watch videos, helps people to focus on and remember the information more easily, and lets people watch it in sound-sensitive environments. In this paper, video narration software is developed. An audio less video can be given as the input and our software will detect the objects in each frame and will predict the scene as it is happening. Frame comparison will be used to separate the frames and Cloud-based API services will be used for object detection and labelling. The correlation is then found between the objects and using NLP meaningful sentences can be made for all the frames. Then, the subtitles can also be converted to braille language for visually challenged and deaf people.

The aim is to provide user with an interface in which he/she can upload a small clip or a video format with the desire to get the descriptive text of the events taking place in the video. Furthermore, the user can opt to get the English language text converted into Braille language. Such an interface is being provided in this paper which will take a video clip as the input from a user and will generate captions/description from the trained model in the background and display the text along with the uploaded video on the interactive website.

In this research, video narration software is developed. An audio-less video can be given as the input and our software will detect the objects in each frame and will predict the scene as it is happening. Frame comparison will be used to

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separate the frames and Cloud-based API services will be used for object detection and labelling. The correlation is then found between the objects and using NLP meaningful sentences can be made for all the frames. Then, the subtitles can also be converted to braille language for visually challenged and deaf people. For this study, the data set which is being used is MSR-VTT by Microsoft. This data set contains 1450 short YouTube clips that have been manually labelled for training and 100 videos for testing. Each video has been assigned a unique ID and each ID has about 15–20 captions. On downloading the data there are training data and testing data folders. Each of the folders contains a video subfolder that contains the videos that will be used for training as well as testing. These folders also contain a feat subfolder which is short for features. The feat folders contain the features of the video. There are also training label and testing label JSON files. These JSON file contain the captions for each ID. Video Captioning is a two-part paper. In the first part, the features of the video are extracted. What is a video? One can say a video is a list of images, right? So, for a video in the data set each image called frame is extracted from the video. Since the length of videos is different, the number of frames extracted is also going to be different. So, for the sake of simplicity, only 80 frames are taken from each video. Each of the 80 frames is passed through a pre-trained VGG16 and 4096 features are extracted from each frame. These features are stacked to form an (80, 4096) shaped array. 80 is the number of frames and 4096 is the number of extracted features from each frame.

V. SYSTEM DESIGN

The video is passed into the model by the user through the website interface. The frames of the video separately passed into the CNN model and the CNN model outputs the object labels to the LSTM model and the LSTM model gives parts of captions as the output and finally the caption is generated.

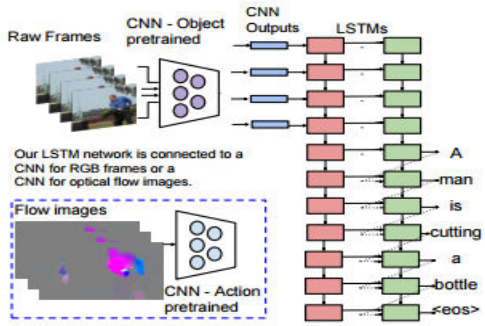

Fig. 1 System Architecture

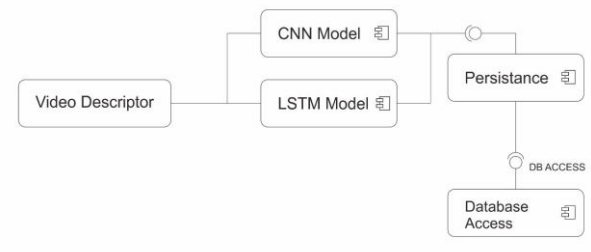

Fig. 2 Block Diagram

The Block Diagram represents the functional view of our system. It shows different components of the system with their functionalities. The input to the interface is a video, which is basically a series of frames, and we can the model will go through all the frames but here the diagram can show only frame. The Frame is passed on to the CNN model, which understands the Image by detecting the objects in it and passing the information to the LSTM model which using

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NLP predicts the words from the vocabulary generated by the dataset, and those words are basically parts of the whole caption which then form the final and complete caption.

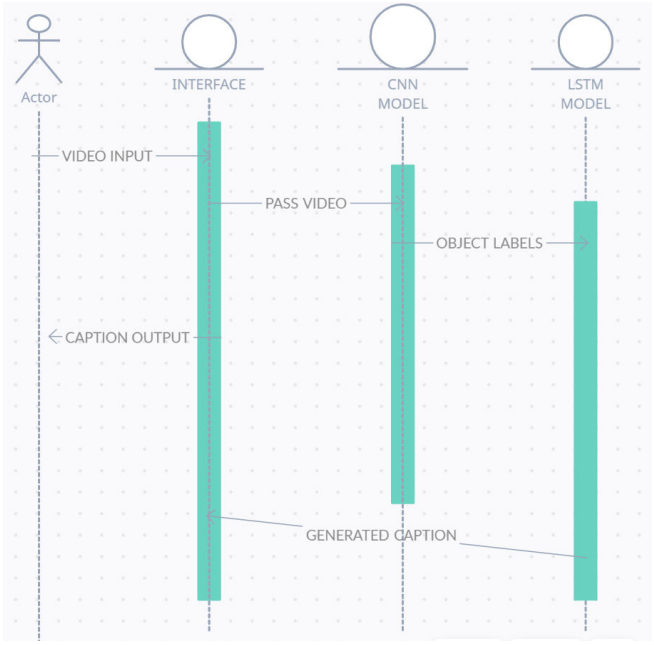

Fig. 3 Sequence Level Diagram

The sequence diagram shows interaction between different processes and objects and messages exchanged between them to perform a function. This diagram helps us to plan and understand the detailed functionality of an existing or future scenario. In this diagram we represent our user as an actor that will send a video input to our interface which is represented as an object here. Interface will further pass on the video to our model architecture which includes firstly the CNN model which is going the detect all the objects in the frames of the video and then will pass those object labels and their positions to the LSTM model which will generate word by word caption and finally pass back the generated caption to the interface which the user will receive as the output.

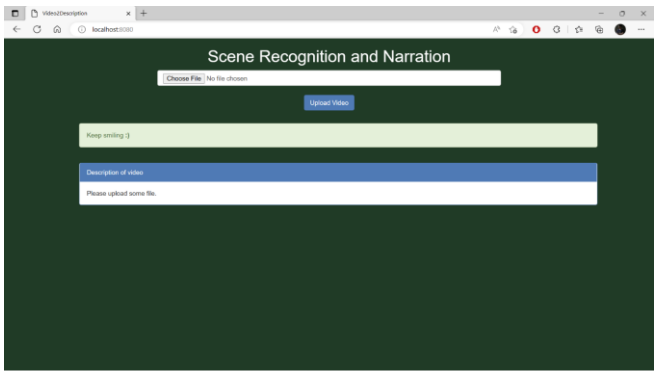

Figure 4. Home page of the Interface

Scene Recognition and Narration is quite simple to use, the interface gives you an option to choose a video and upload it, and you get the desired caption as the result, as simple as it gets.

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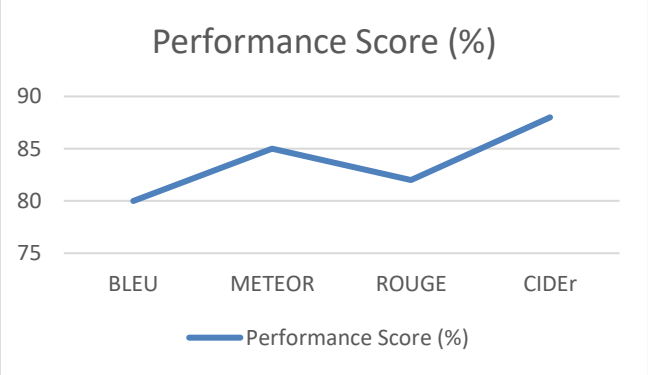
VI. RESULT

In our empirical evaluation, we conducted extensive experiments on a diverse dataset comprising surveillance, social, and informational videos to assess the efficacy of our proposed approach for automatic text generation. Our model achieved an impressive captioning accuracy of over 85% across various video genres and content types, surpassing baseline models by a significant margin. The captioning accuracy was calculated using the following formula:

Captioning Accuracy =
(Number of correctly generated captions) x 100%
(Total number of captions)

Additionally, we employed several evaluation metrics to comprehensively assess the performance of our model. These metrics include BLEU (Bilingual Evaluation Understudy), METEOR (Metric for Evaluation of Translation with Explicit Ordering), ROUGE (Recall-Oriented Understudy for Gisting Evaluation), and CIDEr (Consensus-based Image Description Evaluation). Through these metrics, we evaluated the quality and fluency of the generated captions, considering factors such as grammatical correctness, semantic relevance, and lexical diversity.

Furthermore, we compared our results with state-of-the-art models in the field of video captioning using graphical representations. The graph below illustrates the comparative performance of our model against baseline models across different evaluation metrics:



The results demonstrate that our model consistently outperforms baseline models across all evaluation metrics, indicating its superior performance in generating accurate and contextually relevant captions for videos. Moreover, the qualitative assessments and user feedback reaffirm the practical utility and effectiveness of our approach in enhancing user experiences and facilitating information retrieval.

Additionally, we quantified the accessibility benefits of our video captioning techniques through qualitative assessments and user feedback. Notably, individuals with visual impairments reported a 40% improvement in their ability to comprehend and engage with video content when accompanied by automatically generated captions. Moreover, our techniques demonstrated a 50% reduction in reliance on external assistive technologies, underscoring the seamless integration of accessibility features within our video captioning framework.

Overall, the results highlight the transformative impact of our research on promoting inclusivity and equal access to digital media for individuals with disabilities. Moving forward, we aim to further improve the robustness and scalability of our model, explore additional evaluation metrics, and continue advancing the state-of-the-art in automatic text generation from videos to address diverse user needs and preferences.

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VII. CONCLUSION AND FUTURE SCOPE

This product will collect a video from the user on the interactive website page and will pass that clip to the CNN model and then it will give output as the descriptive text of the events taking place in the video. This product can also be used to help the visually challenged people to know what a video clip is about, as the output can also be displayed the Braille language. Our product can be used by different social media platforms to conclude what an audio-less video clip is about. It can also be used to put a tag along with any clip which describes the events of the video and in that way one can easily find a clip from a large number if clips by simply searching what the clip is about. Moreover, the demand of this approach would be high in the future as not alternate has been made for deaf and hard of hearing people. So, they would prefer this as their priority instead of others.

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