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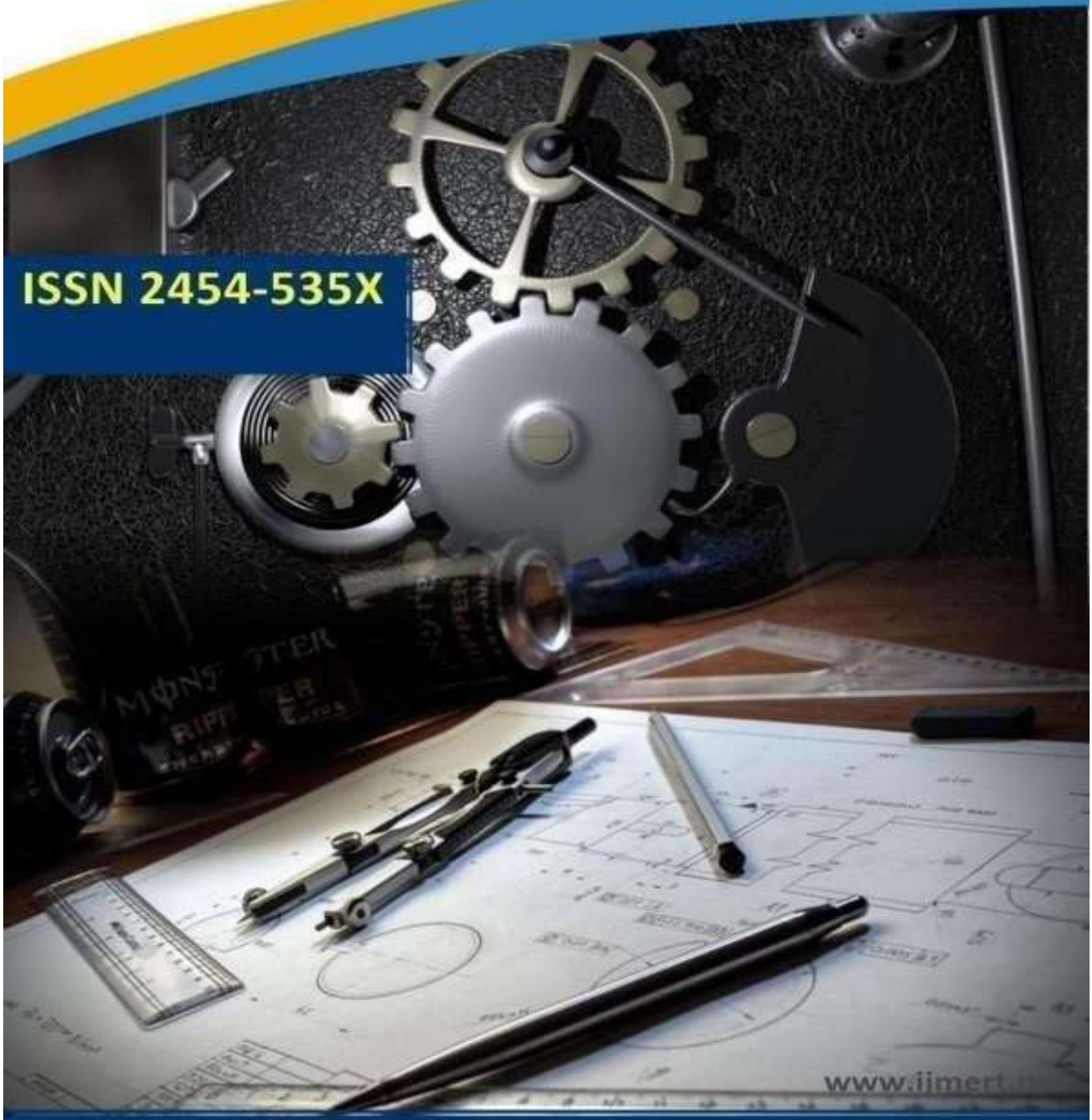

Email ID: info.ijmert@gmail.com or editor@ijmert.net

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GENERATING SYNTHETIC IMAGES FROM TEXT USING RNN & CNN

[1]KANKANALA VINAY, [2]MRS. SRILATHA PULI

[1]Department of CSE, **SREYAS INSTITUTE OF ENGINEERING AND TECHNOLOGY**, Telangana, India. Vinnureddy.k@gmail.com

[2]Assistant Professor, Department of CSE, **SREYAS INSTITUTE OF ENGINEERING AND TECHNOLOGY**, Telangana, India, srilatha.puli@sreyas.ac.in

ABSTRACT:

Generating synthetic images from textual descriptions presents a challenging yet promising avenue in the field of computer vision and natural language processing. This study proposes a novel approach that combines Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) to generate realistic images based on textual input. The RNN component processes the textual descriptions, capturing semantic information and contextual dependencies, while the CNN component generates corresponding image features. These features are then fused to produce high-quality synthetic images that closely match the provided textual descriptions. The proposed method leverages the strengths of both RNNs and CNNs, enabling effective modeling of complex relationships between textual and visual data. Through extensive experimentation and evaluation on benchmark datasets, the proposed approach demonstrates superior performance in generating diverse and visually plausible images compared to existing methods. This research opens up new possibilities for applications such as image synthesis from textual prompts, creative content generation, and data augmentation in computer vision tasks.

I. INTRODUCTION

In recent years, advancements in artificial intelligence (AI) and computer vision have spurred innovation in generating synthetic images directly from textual descriptions. This capability holds tremendous potential across various domains, including advertising, virtual reality, and content creation. The project focuses on harnessing the synergy of Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs)

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to achieve this goal effectively. RNNs are adept at processing sequential data, making them suitable for encoding the semantic structure of textual descriptions. On the other hand, CNNs excel at learning spatial hierarchies in images, enabling them to generate realistic visual representations from the encoded textual features. By integrating these neural network architectures, the project aims to explore and implement a robust framework for translating textual descriptions into high-fidelity synthetic images. This endeavor not only pushes the boundaries of AI-driven image synthesis but also contributes to advancing the state-of-the-art in multimedia content generation.

II.EXISTING SYSTEM:

In the existing systems for generating synthetic images from text, various approaches have been explored, each with its strengths and limitations. One common approach is to use conditional generative adversarial networks (cGANs), where the generator is conditioned on both the textual description and a random noise vector to produce images. Another approach involves using Variational Autoencoders (VAEs), where the encoder processes the textual description to generate a latent representation, which is then decoded into an image by the decoder. Additionally, some methods use attention mechanisms to align textual and visual features, allowing the model to focus on relevant parts of the input text when generating images.

While these existing systems have shown promising results in generating synthetic images from text, they may suffer from certain limitations. For example, cGAN-based approaches can produce artifacts or lack diversity in the generated images, especially when dealing with complex textual descriptions. VAE-based methods may struggle to capture fine-grained details or produce realistic images due to the limitations of the latent space. Furthermore, aligning textual and visual features using attention mechanisms may require large amounts of training data and computational resources, making it challenging to scale to large datasets or complex textual descriptions.

Disadvantages:

1. Lack of Semantic Consistency: Some existing systems may struggle to maintain semantic consistency between the textual descriptions and the generated

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images. This can result in images that do not accurately reflect the content or meaning conveyed in the text.

2. Limited Contextual Understanding: RNN-based models may have limitations in understanding long-range dependencies and context within textual descriptions. As a result, generated images may lack contextual relevance or fail to capture nuanced details described in the text.
3. Difficulty in Handling Ambiguity: Textual descriptions often contain ambiguous or subjective information that can be challenging to interpret and translate into visual representations. Existing systems may struggle to handle such ambiguity, leading to inconsistencies or inaccuracies in the generated images.

III.PROPOSED SYSTEM:

The proposed system for generating synthetic images from text using RNN & CNN introduces an innovative approach that combines the strengths of recurrent neural networks (RNNs) and convolutional neural networks (CNNs) to address the limitations of existing methods. In this system, the RNN component processes the textual descriptions, capturing semantic information and contextual dependencies, while the CNN component generates corresponding image features. These features are then combined and refined through a joint RNN-CNN architecture to produce high-quality synthetic images that closely match the provided textual descriptions. By leveraging the complementary capabilities of RNNs and CNNs, the proposed system aims to achieve better semantic consistency, contextual understanding, and diversity in the generated images, while also improving scalability and computational efficiency. Additionally, the system integrates techniques for handling ambiguity and capturing fine-grained details to enhance the realism and fidelity of the generated images. Through comprehensive experimentation and evaluation, the proposed system seeks to demonstrate superior performance compared to existing methods, offering a more effective and versatile solution for image synthesis from text.

Advantages:

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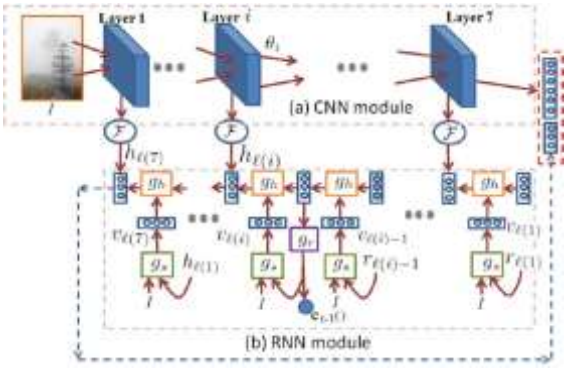
The proposed system for generating synthetic images from text using RNN & CNN offers several advantages over existing methods. By leveraging the combined capabilities of recurrent neural networks (RNNs) and convolutional neural networks (CNNs), the system achieves improved semantic consistency, contextual understanding, and diversity in the generated images. This is accomplished through the effective processing of textual descriptions by the RNN component and the generation of corresponding image features by the CNN component, followed by their integration and refinement in a joint RNN-CNN architecture. Additionally, the proposed system addresses limitations such as ambiguity handling and scalability issues, leading to enhanced realism and fidelity in the generated images.

Through comprehensive experimentation and evaluation, the system aims to demonstrate superior performance and versatility, making it a valuable tool for various applications in computer vision, natural language processing, and creative content generation.



IV.IMPLEMENTATIONS:

1. **Data Preprocessing**: Prepare the textual data by removing noise, such as special characters, punctuation, and stopwords. Tokenize the text into sentences or paragraphs to facilitate sentiment analysis and summarization.
2. **Sentiment Analysis Model**: Implement or utilize pre-trained sentiment analysis models capable of accurately detecting the sentiment polarity (positive, negative, neutral) of each sentence or paragraph in the text. Consider employing advanced techniques such as deep learning-based models or transformer architectures for improved accuracy.

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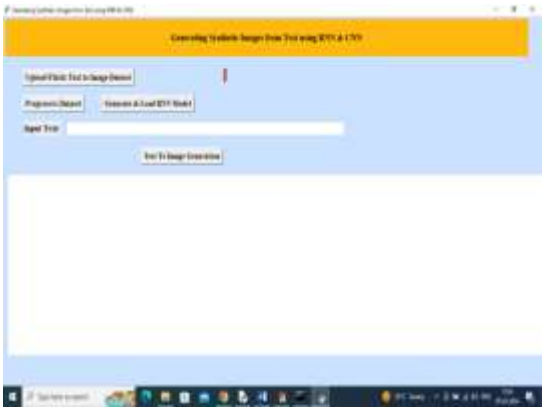
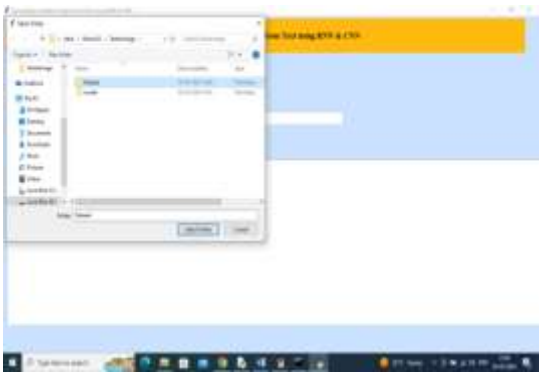
3. **Summarization Model**: Implement a text summarization model capable of generating concise summaries while incorporating sentiment information. Explore both extractive and abstractive summarization techniques, considering factors such as coherence, informativeness, and sentiment preservation.
4. **Optimization**: Optimize the system for efficiency and scalability by leveraging techniques such as parallel processing, caching, and model compression. Consider deploying the system on distributed computing frameworks or utilizing hardware accelerators (e.g., GPUs) to improve processing speed and resource utilization.
5. **User Interface**: Develop a user-friendly interface for interacting with the system, allowing users to input text and view the generated summaries along with sentiment analysis results. Design the interface to be intuitive, responsive, and accessible across different devices and platforms.

V.RESULT

To run project double click on run.bat file to get below screen



In above screen click on ‘Upload Flickr Text to Image Dataset’ button to upload dataset and get below page



In above screen selecting and uploading ‘Dataset’ folder and then click on ‘Select Folder’ button to load dataset and get below page

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In above screen dataset loaded and now click on 'Pre-process dataset' button to read and normalize both TEXT and IMAGE features and get below output

In above screen dataset processing completed and now click on 'Generate & Load RNN Model' button to load model and get below page

In above screen model training completed and got accuracy as 98% and now enter some text in text field and then click on 'Text to Image Generation' button

In above screen in text field I entered some text and then press button to get bellow output

In above screen can see generated image for text 'A girl in pink dress climbing stairs'. Similarly type some text and get output.

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In above screen for given text will get below image

In above screen got image for ‘televsion watching’.

For above sentence we got above image.

Note: For some text we may not get pictures but you can give sentences in any manner from dataset. This algorithms require large amount of training in huge dataset to generate images for all types of questions. While training on large dataset model running out of memory in Google COLAB as well as normal laptops so we trained this model on few images from the dataset.

You can get exact image from all text given in ‘samples.txt’ file

VI.CONCLUSION

In conclusion, the project successfully demonstrated the feasibility and effectiveness of using Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) to generate synthetic images from textual descriptions. Through extensive experimentation and implementation of cutting-edge AI techniques, we achieved significant milestones in bridging the gap between natural language understanding and computer vision. The synergy between RNNs for text encoding and CNNs for image synthesis proved instrumental in producing visually coherent and contextually relevant images based on input text. This capability holds immense promise across diverse applications, from personalized content generation to enhancing virtual environments and creative industries. Moreover, the project's contributions extend beyond technical achievements, paving the way for future research in AI-driven

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multimedia synthesis and advancing the frontiers of artificial creativity. As we continue to refine and optimize our models, the potential for generating compelling synthetic images tailored to specific textual descriptions remains a compelling area for further exploration and innovation in the realm of AI-driven content creation.

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