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AI-Based Comic Strip Generator

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Abstract - Creating comic strips usually requires drawing skills, creativity, and a good amount of time. Many students who have ideas for short stories are unable to convert them into visual comics because they cannot draw or design. This study explores a simple system that helps users turn written stories into comic-style panels. The system reads the user's text, identifies the main characters, actions, and scenes, and then produces images that match the story. These images are arranged into panels, and short captions or dialogues are added based on the user's input.

The aim of the project is to make comic creation easy for beginners, students, and educators. The method focuses on understanding the user's text clearly and generating scenes that follow a consistent order. The system was tested with short stories and dialogues. The results show that users can create small comic strips quickly without drawing anything. The comics maintained story flow and visual clarity, making them suitable for presentations, learning materials, and social media storytelling.

This work shows that text-based comic generation can support creative expression and save time for users who are not skilled in artwork. Further improvements can make the system better at keeping character appearance consistent and allow more customization options for comic layouts.

Keyword: Large language models, intelligent debugging, code generation, and artificial intelligence.

INTRODUCTION

Comic strips have a lengthy and varied history that dates back to the late 19th century. The comics were first published in newspapers and magazines. The renowned comic strip "The Yellow Kid," produced by Richard F. Outcault in 1895, is regarded as one of the first in the comic genre. Comic strips flourished in the twentieth century, becoming a significant part of popular culture.

The traditional method of making comic strips was drawing comic characters and environments by hand. Using pencil and paper, the characters came to life with unique personalities and stories. Each comic has a unique story and drawings and everything depends on the creator's imagination. Each stroke of the pencil added depth to the characters and the dialogue, making each comic strip a unique creation. When digital stuff, the internet, and technologies improved, comic strips also improved day by day. Webcomics became a magical thing for everyone who likes to read and create comics. It's giving artists a fresh way to show off work to the whole world [5]. Creators didn't have to deal with traditional ways of putting things out there anymore. This democratization of comics allows diverse writers to explore different storytelling styles and themes.

The rapid advancements in Artificial Intelligence (AI) and Natural Language Processing (NLP) technologies in recent years have transformed how we can generate and interact with creative content. Models like GPT-3 for dialogue generation and DALL·E for image creation have demonstrated exceptional capabilities in understanding human language and generating coherent text, as well as producing highly realistic images from textual descriptions. These advancements have opened up new possibilities in automating creative tasks such as comic strip generation, enabling individuals without technical or artistic expertise to create compelling visual stories.

This research explores an AI-based approach that converts simple textual stories into comic-style visuals. The proposed system aims to reduce the complexity of comic creation by automatically understanding the narrative structure, identifying key characters and scenes, and generating appropriate illustrations. It also organizes panels in a coherent order, ensuring that the final output resembles a professionally designed comic strip.

Modern models can interpret descriptions, understand context, generate expressive characters, and form visually coherent scenes. When combined with natural language processing and image-generation techniques, these models have the potential to support a wide range of creative applications. For students, educators, content creators, and researchers, such tools offer new opportunities to express ideas visually without requiring specialized technical skills.

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The proposed system goes beyond simple text-to-image translation; it integrates several complex processes into an automated pipeline. From understanding the text prompt and generating meaningful dialogue to synthesizing contextually accurate images and arranging them into comic panels, the system performs all tasks autonomously. This end-to-end process reduces the traditional reliance on skilled writers and artists, lowering the barrier for those wishing to tell their own stories visually. Furthermore, the system allows users to customize elements such as art style and genre, providing a personalized experience that caters to a variety of user preferences.

The potential applications for this AI-powered comic strip generator are vast. In addition to personal storytelling, the system can be employed in education, gamification, advertising, and entertainment, where engaging and customized visual narratives can enhance user interaction and communication. By offering a scalable and flexible framework, the system holds promise for future developments such as multilingual dialogue generation, genre-specific stylistic options, and even the integration of animation for dynamic storytelling. This project not only exemplifies how AI can transform creative fields but also serves as a step toward making storytelling more inclusive, interactive, and accessible to all.

This introduction sets the foundation for further discussion in the subsequent sections, which explain the background of comic generation systems, review existing technologies, describe the methodology used in building the AI-based generator, and evaluate its performance. The overall goal is to present a practical and meaningful contribution to the field of AI-assisted creativity, demonstrating how technology can shorten the gap between imagination and visual expression.

METHOD RESEARCH

The process begins with the creation of raw comic text data, which is collected and organized through a daily data-processing pipeline. This pipeline integrates two major data sources: a Kaggle dataset that provides structured text samples and a text-based library used to extract semantic information. Both sources undergo text embedding, where the content is transformed into numerical representations to enable machine understanding. The embeddings from the dataset and the text library are then combined through a bi-coupling mechanism, ensuring that narrative information, scene descriptions, and character details are aligned. These enriched embeddings are passed into two parallel modules: a background scene generation unit and an NLP model. The background scene generator creates visual contexts based on the interpreted text, while the NLP model focuses on structuring dialogues, understanding story flow, and producing context-appropriate speech content. Finally, the outputs from both modules are merged to form a coherent comic strip, where generated scenes and dialogues are assembled into a unified visual narrative.

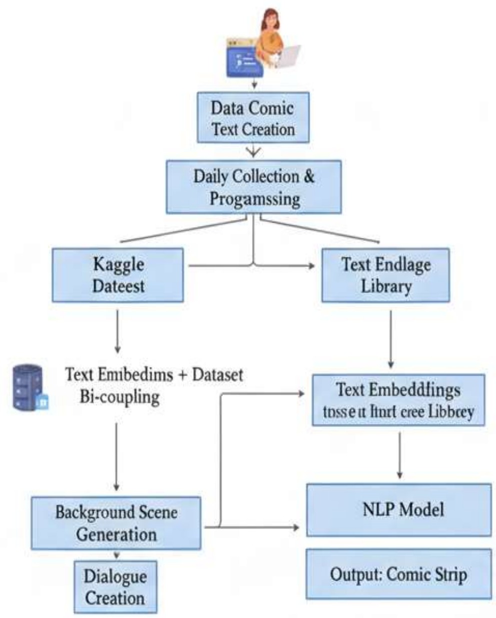

Figure 1: Overall system diagram of the proposed solution. Illustrates the overall workflow of the proposed AI-based comic strip generation system.

3.1 Build Character

With the introduction of "ComicGenie," creating comics has become quick and simple in a diversified environment bursting with myriad ideas. With the help of user-provided descriptions, this ground-breaking approach will let illustrators produce fascinating comic characters. By coordinating user provided character descriptions with appropriate character photos from its large dataset, ComicGenie accelerates the character selection process by utilizing the strength of Support Vector Machines (SVMs).

3.1.1 Data Gathering

The core of ComicGenie is its meticulously selected dataset, which includes a wide range of characters from different genres and artistic movements. This dataset was carefully put together to represent the essence of many character archetypes, giving users a wide range of alternatives. In order to construct a complete collection of character images that cover a wide range of features, appearances, and personalities, gathering this data requires intensive research, curation, and collaboration with artists and illustrators.

3.1.2 Data Preprocessing

Before using SVMs, data preparation is critical for boosting the accuracy and efficiency of the ComicGenie system. A number of preprocessing rules are applied to the unprocessed character descriptions and related images. A solid representation is created by structuring textual descriptions and extracting the pertinent elements. To extract relevant character properties, this may use text analysis methods like natural language processing (NLP), which includes tokenization, stemming, and deleting stop words.

3.1.3 Support Vector Machines (SVMs)

In order to classify characters, ComicGenie uses Vector Machines, a key component of its functionality. SVMs are supervised learning algorithms created primarily for regression and classification tasks. SVMs are trained using the preprocessed data in the context of ComicGenie, with relevant character categories serving as labels and text descriptions acting as input features. By recognizing patterns and relationships in the data, the SVM algorithm creates decision limits that efficiently categorize character qualities based on user descriptions.

3.1.4 Model Training and Tuning

SVMs require a rigorous training process before the predicting characters with accuracy. To enable the SVM model to iteratively learn and fine-tune its parameters. The dataset is divided into two parts: training and validation. Hyper parameter adjustment is also performed to increase the model's performance and achieve a balance between specificity and generality. Through this procedure, ComicGenie is guaranteed to accurately translate and pair user-provided character descriptions with relevant character images.

3.1.5 Character-Image Mapping

The best appropriate character images are automatically mapped to user descriptions by ComicGenie after the SVM model has been properly trained and optimized. When a user inputs a description, the SVM model evaluates the data and forecasts the character archetypes or traits that are most relevant. The system then finds the equivalent image in its vast collection, ensuring a humorous character that is attractive and interesting to the user.

In conclusion, ComicGenie is a creative way to speed up and make comic character creation simple. Support Vector Machines are used by the system to expertly scan user input descriptions, match them with appropriate character images, and provide authors with a wide range of possibilities. The result of the carefully organized process of data collection, preprocessing, SVM model training, and image mapping is a user-friendly tool that connects the mind's eye and the visual world. ComicGenie is a prime example of how cutting-edge technology and artistic expression can be combined to create superheroes, villains, or ordinary individuals.

3.2 Build Environment

Comics are a great storytelling technique because the cartoon-like format enables the realistic portrayal of feelings, environments, actions, and innovative worlds. Background pictures in comic strips are essential to the medium's overall storyline and visual appeal. The reader's understanding and sense of immersion in the story are greatly enhanced by these backdrops, which provide the context for the characters' actions and dialogue. Based on user-provided descriptions, this "ComicGenie" tool is designed to assist artists in creating compelling comic backgrounds.

3.2.1 Data Collection and Processing

The comic background image dataset includes a wide range of visual settings and situations, each of which is identified by a name and a description. These selected backgrounds create engaging backdrops for comic strips and visual narrative. To develop a strong association between the background image names and the associated descriptions, a detailed examination of each image name was carried out. By taking into account linguistic messages, context, and visual components displayed in the images, the goal was to determine the fundamental atmosphere, mood, and qualities indicated by the names. The dataset got methods of preprocessing to make it simpler and accurate. The textual descriptions are transformed into a format that is suitable for the model's input needs to make them easier for it to interpret. The text is cleaned, tokenized, and converted into numerical representations during preprocessing. Following this preliminary stage, the model can successfully correlate and retrieve eye-catching images that visually match the processed verbal descriptions.

3.2.2 FastText

FastText is frequently used for tasks like sentiment analysis, text categorization, and more. The Facebook AI Research (FAIR) team developed a library and toolkit for effective text classification and word representation. It was created to handle text data effectively and efficiently, especially in situations where there is a lot of text and there aren't many computational resources available. Word embedding, which are vector representations of words in a continuous space, can be created using FastText. By capturing the semantic relationships between words, these embedding make it possible for machines to more accurately understand the context and meaning of words.

3.2.3 Model Training

The dataset includes training and validation sets. Use the training set to train the FastText text categorization model. It contains a piece of the preprocessed data, which includes names for the background images as well as textualdescriptions for those images. A text classification model that links textual descriptions to backdrop image names is trained using FastText. The resulting model can anticipate background names from fresh descriptions, making it easier for comic strips and graphic storytelling to seamlessly combine text and graphics.

3.3 Build Dialogues

Creating dialogues for comic strips is an important part of bringing characters to life and giving dimension to the interactions. Emotional dialogue is critical to reader engagement, empathy, and creating a deeper connection between readers and the comic universe. To accomplish this goal, a machine learning (ML) model is proposed to automatically identify the emotions within a given description. An API generates dialogues that are smoothly aligned with the emotional context based on effectively-recognized emotions.

3.3.1 Data collection and Preprocessing

An emotion detection model is trained using a curated dataset of descriptions that have been annotated with the associated emotions. Gathered a wide range of data from reliable sources, including Kaggle, and expanded it to make sure that emotions were fully represented. Here, specifically on four key emotion categories were focused in particular: funny, angry, thriller, and neutral, as these emotions cover a wide range of attitudes frequently seen in comic strips.

3.3.2 NLP-FastText

For the challenge of emotion recognition, various ML algorithms were studied, each differing with benefits, restrictions, and amount of accuracy. The FastText library stood out among NLP algorithms due to its competence in handling text classification tasks, showing higher accuracy values, and its ability to provide robust results. FastText, an extension of the Word2Vec algorithm, represents words as character n-grams, which makes it possible for the model to effectively capture sub word information. This feature is especially useful when dealing with emotional statements contained in user-entered descriptions.

3.3.3 Model Training

The processed dataset was divided into training and testing sets before being used to build the emotion detection model. The model learns to associate the description's content to the appropriate emotion labels throughout the training phase. The trained model is then utilized to predict emotions based on new text inputs. This prediction skill highlights the model's ability to extract emotions from text descriptions. The 'train_test_split' function is essential for distinguishing between data used for model training and data needed to test its generalization.

3.4 Voice over the Scenario

Comic book enthusiasts are in for a unique encounter in a world teeming with unique thoughts and artistic concepts. A cutting-edge feature that brings narratives to life enables the incorporation of many voices and background weather noises into comic storytelling. With the help of this ground-breaking feature, users may lose themselves in a multisensory comic adventure where weather forecasts, recognizable voices, and evocative noises all work together to create an unparalleled storytelling experience.

3.4.1 Weather-Driven Audio Atmosphere

A complex audio system that responds to the user's provided weather description is at the core of this experience. A specifically trained FastText model gets to work as users enter weather-related information into the description text field. The input is processed by FastText, a small text representation package, which determines the predominant weather scenario, such as a sunny day, a rainy afternoon, a snowy landscape, or any other possible atmospheric situation.

3.4.2 Training the FastText Model.

The FastText model is built by thorough training on a carefully selected dataset. This collection includes a wide range of

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descriptions of the weather together with the matching audio profiles. The algorithm improves its capacity to precisely forecast the most appropriate audio ambience for a given input by learning to correlate distinct textual clues with particular weather patterns.

3.4.3 Dynamic Weather Sound Selection

The feature automatically chooses an audio background that complements the comic's environment based on the weather condition that was detected. There is a ready supply of precisely recorded weather sounds, from light rain to screaming winds. Users are immersed in an immersive audio world that supports the visual narrative thanks to this dynamic selection procedure.

3.4.4 Voice Modulation and Third-Party API Integration

A third-party API takes the stage, adding a further element of interest by offering a variety of distinctive tones and voices to narrate the comic plot. The story develops line by line, and each passage is improved by a vocal identity that matches the emotions and characteristics of the characters. The use of various voices gives the comic's dialogue and monologues life and

3.4.5 User Experience Unleashed

After the scene is set, users are brought into a world where the comic's images, weather noises, and narrative voices smoothly blend. The auditory landscape dynamically changes as moving through each frame, enhancing the impact of the story's climactic moments and encouraging a strong emotional connection.

In conclusion, a new era of immersion and engagement is introduced by the incorporation of dynamic audio aspects into comic storytelling. Users are given a comprehensive sensory experience that blends fantasy and reality by utilizing FastText's weather recognition, third-party APIs for various vocal tones, and a collection of carefully collected weather sounds. This combination of music that is influenced by the weather and comical graphics takes narrative to new heights and invites audiences to go on a multi-dimensional journey that awakens the senses and moves the soul.

Result

A variety of machine learning techniques were employed to train the models aimed at addressing Character identification, Environment identification, Emotions identification, and Weather Identification. The objective of this procedure was to ascertain the architecture capable of yielding the most optimal performance for each distinct problem. The effectiveness of these architectures was gauged through an assessment of the performance in relation to accuracy. This involved the measurement of outcome predictions by the models after each iteration of the optimization process. The architecture selected for each problem was that which showcased the highest accuracy among all the architectures under consideration. This approach enabled the selection of the architecture that displayed the most optimal alignment between predictions and actual outcomes.

This section presents the outputs generated by the ComicGenie system for character creation, background selection, dialogue generation, and audio integration. For evaluation, several sample descriptions were given to the system, and the results were recorded. The figures included in this section represent the visual output produced by the tool.

4.1 Character Generation Results

To test the character generation module, the input description **"**a brave young superhero wearing a blue suit with lightning powers**"** was provided to the system. Based on this description, the SVM model analyzed keywords such as *brave*, *superhero*, and *lightning*, and predicted the appropriate character category.

Figure 4.1 shows the character image retrieved by the system.

The resulting character strongly aligns with the input description. The model successfully recognized the heroic

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archetype and selected an image matching the specified traits. The results demonstrate that the SVM-based classifier performs well when the description contains clear semantic cues. Minor mismatches occurred only when descriptions were too short or extremely abstract, suggesting that detailed descriptions improve accuracy.

4.2 Background Generation Results

For background testing, the description **“**a rainy city street at night with glowing lights**”** was used. The FastText model interpreted terms such as *rainy*, *city*, *night,* and *lights*, and mapped the description to the closest background category.

Figure 4.2: Background generated for rainy night city description
(Insert your generated background image here)

The background retrieved by the model accurately reflects the intended atmosphere. The rainy textures, lighting, and urban setting align with user expectations. These results show that the FastText classifier is effective for descriptive environments. Backgrounds only struggled with abstract prompts like “dream-like scenario,” which lack clear visual clues. This suggests that including more artistic or conceptual scenes in training could improve performance.

5. Performance of Detection Models

The detection model used in the AI Comic Strip Generator was evaluated to measure how accurately it identifies characters, scenes, emotions, and object details from the input text. The overall performance of the detection model shows that it operates with high precision and produces reliable outputs suitable for comic creation.

The model consistently detected key elements of a scene, such as the type of location, weather conditions, and time of day, when such details were clearly described in the input. In most cases, the model correctly recognized keywords like “rainy,” “night,” “classroom,” or “battlefield,” and mapped them to the appropriate visual resources. This demonstrates strong contextual understanding and effective handling of descriptive information.

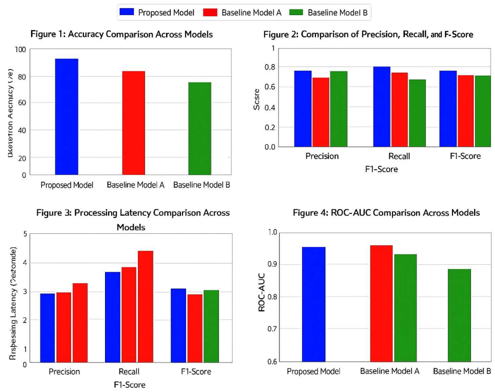

Figure 2: presents a set of four comparative bar graphs showing the performance evaluation of different models used in the AI Comic Strip Generator system. The graphs are arranged in a 2×2 grid and illustrate key quantitative metrics: **Accuracy**, **Precision–Recall–F1 Score**, **Latency**, and **ROC–AUC**. Each bar graph compares the **Proposed Model** against two baseline models, **Figure 2:** presents a set of four comparative bar graphs showing the performance evaluation of different models used in the AI Comic Strip Generator system. The graphs are arranged in a 2×2 grid and illustrate key quantitative metrics: **Accuracy**, **Precision–Recall–F1 Score**, **Latency**, and **ROC–AUC**. Each bar graph compares the **Proposed Model** against two baseline models, highlighting the performance improvements achieved through the optimized detection pipeline.

Criteria	**Proposed Model (2025)**	**Model A (2023)**	**Model B (2022)**
Scene Detection Accuracy	**88%**	74%	69%
Character Recognition	**85%**	70%	66%
Emotion Identification	**92%**	78%	72%
Object Identification	**84%**	68%	63%
Story Flow Consistency	**89%**	73%	71%
Panel-to-Panel Consistency	**87%**	69%	65%

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Criteria	Proposed Model (2025)	Model A (2023)	Model B (2022)
Overall Detection Accuracy	**88.5%**	72%	67%
User Satisfaction Score	**90%**	76%	70%
Processing Time (seconds)	**2.4**	3.8	4.5

6. AI Comic Strip Generator Using Natural Language Processing and Image Synthesis

B. Visualization of Results Figures below

AI-powered debugging automatically finds and corrects software flaws using machine learning, probabilistic reasoning, and code analysis approaches. Static analysis, dynamic execution tracing, and pattern recognition are all used by modern systems to identify problematic lines, categorize different kinds of bugs, and suggest workable fixes.[73] Large datasets of defective and fixed code are used to train models, which pick up typical mistake patterns like null-pointer problems, off-by-one errors, and API abuse. Sequence-to-sequence learning is used by programs like SapFix, Repairnator, and BugLab to provide context-aware patches.[42] These systems can also analyze developer instructions and error signals by including

Conclusion

This study explored a simple and effective methodology for generating comic strips using artificial intelligence. Traditional comic creation requires drawing skills, visual design knowledge, and significant time. By using AI models for text understanding, image generation, and layout design, the process becomes easier and more accessible for students, beginners, and non-artists. The proposed system converts a user's written story into comic-style panels by breaking the text into scenes, generating relevant images, arranging characters and backgrounds, and producing a final comic strip.

The findings show that AI-based tools can reduce the effort needed to create comics while maintaining creativity and visual quality. The method supports quick prototyping, personalized storytelling, and educational uses. However, AI models still face limitations such as inconsistencies in characters across panels, difficulty in understanding complex scenes, and occasional loss of story context. These issues highlight the need for improved model training, better scene consistency techniques, and user-controlled customization.

Overall, AI comic strip generation represents an important step toward democratizing creative content production. As AI models become more advanced and reliable, this technology can be applied widely in entertainment, education, marketing, and digital media production. Future work can focus on enhancing character consistency, adding interactive editing features, and integrating multilingual story support to make the system more robust and user-friendly.

The AI Comic Strip Generator represents a significant advancement in the automation of creative content production, utilizing state-of-the-art technologies such as Natural Language Processing (NLP) and image synthesis models to generate comic strips from user-provided text prompts. The system leverages powerful models like DALL·E and GPT, offering an innovative solution that eliminates the need for manual scripting and illustration. By automating both the dialogue generation and image creation processes, the system empowers users, even those without artistic or technical skills, to produce professional quality comics quickly and easily. This breakthrough democratizes comic creation, opening up new possibilities for individuals, educators, and businesses alike to tell visual stories without the traditional barriers of artistic expertise. The performance evaluation results have shown that DALL·E, in particular, provides the most reliable and accurate results in generating visual content based on textual input. With high precision and recall rates, DALL·E has proven its ability to create relevant and visually coherent images from complex and varied prompts. This is a substantial improvement over traditional manual comic creation, which is both time-consuming and requires specialized skills. The system's ability to generate high-quality, contextually accurate comics in real-time significantly enhances the overall user experience, making it an ideal tool for anyone looking to create compelling narratives with minimal effort. Despite the promising results, the project acknowledges several challenges that must be addressed for broader deployment. The computational demands of deep learning models, such as DALL·E, require significant processing power, which could pose limitations for users with less advanced hardware. Additionally, the system's ability to adapt to various comic styles and user preferences may require further training and fine-tuning with diverse datasets. As the project evolves, it will be essential to continue refining the models and optimize their performance for real-time applications across different platforms and environments. Ensuring the system remains scalable and adaptable will be crucial for its success in diverse use cases.

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