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AI Based Video Insights Generator

Sk. Wasim Akram[1], Y. Bindu Varsha[2], P. Sambasivarao[3], P. Snehal Kumar[4], V. Charan Sai Venkat[5]

Assistant Professor, Dept. of. CSE, VVIT, GUNTUR, AP, INDIA[1]

Student, Dept.of.CSE Artificial Intelligence and Machine Learning, VVIT, GUNTUR, AP, INDIA[2,3,4,5]

Abstract: This research presents two integrated systems designed to extract and summarize information from videos and text. The first system, titled AI Based Video Insights Generator, leverages deep learning techniques, particularly Long Short-Term Memory (LSTM) networks, for detecting themes from video and textual content. This approach incorporates speech-to-text transcription, timestamp extraction from videos, and an interactive question-answering capability. Additionally, the system supports multilingual theme detection, enabling translations via APIs.

Key features of the system include:

- User Authentication: Provides a user registration, login, and feedback mechanism.
- Data Preprocessing: Includes tokenization, stop word removal, and lemmatization.
- Theme Detection: Detects themes from both videos and text, using APIs for audio transcription and video timestamp extraction, coupled with LSTM, Conv1D, MaxPooling1D, and Batch Normalization layers for classification.
- Interactive Q&A System: Users can ask questions about the video content, and the system generates relevant responses. • Multilingual Support: The detected themes can be translated into multiple languages via APIs.
- Training Optimization: Implements Early Stopping and Model Checkpoint techniques for improved model performance. • Evaluation Metrics: The model's performance is assessed using standard classification metrics.

The second system, titled Pre-train Summarization, focuses on summarizing text, particularly from transcribed video content. This system utilizes pre-trained transformer models to generate concise summaries of long documents or videos, making it a valuable tool for quick insight extraction. It supports speech-to-text transcription, text summarization, and multilingual translation.

Key features of the Pre-train Summarization system include:

- Dependency Installation: The system uses Hugging Face Transformers, PyTorch, TensorFlow, and PEFT for model fine-tuning.
- Data Processing: Extracts and preprocesses text from YouTube videos, Google Drive videos, or user-uploaded content.
- Transformer-Based Summarization: Implements models such as T5, Pegasus, or BART to generate text summaries.

Keywords: LSTM, Multi-Level Classification, Theme Detection, Text Summarization, Video Transcription, Speech-to-Text, Transformer Models, Multilingual Support, Pre-trained Models, ROUGE Metrics.

1. INTRODUCTION

The growing demand for efficient content analysis from diverse sources has led to the development of advanced techniques in natural language processing (NLP) and deep learning. Detecting themes from various forms of content, such as videos and text, has become an essential task in fields like content curation, information retrieval, and multimedia analysis. To address these challenges, we propose two powerful systems: the LSTM-90 Multi-Level Classification and the Pretrain Summarization approach.

The AI Based Video Insights Generator is designed to detect themes from both textual and video content. Using an LSTM-based deep learning approach, it not only detects themes from written text but also processes YouTube videos, Google Drive videos, or locally uploaded videos. This system combines speech-to-text transcription and video timestamp extraction, allowing it to extract valuable insights from multimedia sources. An additional feature of this system is its ability to answer user queries regarding the video content, making it an interactive tool for content understanding. The system also provides multilingual theme detection through API integration, enabling broader accessibility across different languages..

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The second system, Pre-train Summarization, focuses on summarizing lengthy text, particularly transcribed video content. By leveraging pre-trained transformer models, it is capable of generating concise and meaningful summaries from extensive documents or video transcripts. This system helps users quickly grasp key insights from videos or long-form content without needing to read or watch everything in its entirety. Like the AI Based Video Insights Generator system, it also supports speech-to-text transcription and multilingual translation, making it a versatile tool for summarization across different languages and formats. Both systems employ advanced deep learning techniques and powerful natural language models, allowing them to perform complex tasks such as theme detection, summarization, and real-time user interaction. With the integration of cutting edge technologies, these systems provide a comprehensive solution for content analysis and understanding in today's multimedia-rich digital environment.

2. LITERATURE SURVEY

The task of theme detection from multimedia sources such as videos and text has garnered significant attention in recent years. With the advent of deep learning and natural language processing (NLP) techniques, researchers have made substantial progress in extracting meaningful content from large and diverse datasets. One of the primary methods for achieving effective theme detection is through the use of Recurrent Neural Networks (RNNs), particularly Long Short Term Memory (LSTM) networks, which have shown promise in capturing temporal dependencies in sequential data like text and speech.

Several studies have focused on applying LSTM networks to text-based theme detection. For instance, Zhang et al. (2015) introduced a method for classifying text into multiple categories using LSTM networks, demonstrating its superiority over traditional models like Support Vector Machines (SVM) in capturing long-term dependencies . Their approach paved the way for further advancements in multi-label classification and theme detection tasks. Building on this, Yu et al. (2018) applied LSTMs for multi-label classification in text data, emphasizing the importance of using deep learning techniques for understanding contextual information in documents .

In the context of multimedia content, recent research has combined LSTM models with other architectures, such as Convolutional Neural Networks (CNNs), to enhance performance in detecting themes from videos. For example, Vaswani et al. (2017) developed the Transformer model, which outperformed LSTM in various NLP tasks by using self-attention mechanisms . Despite the success of Transformers in many NLP tasks, LSTMs remain a popular choice for video and speech-based applications, as demonstrated by Li et al. (2019), who combined LSTMs with CNNs to classify themes from YouTube videos . Their work highlighted the potential of using both audio and visual features to improve the accuracy of theme detection in video content.

Moreover, theme detection from videos often requires integrating speech-to-text transcription to convert audio content into textual form. Recent advances in automatic speech recognition (ASR) have significantly improved the performance of transcription systems. Models like DeepSpeech (Hannun et al., 2014) and wav2vec (Baevski et al., 2020) have become crucial tools in processing spoken content for theme detection tasks , . These models, along with the integration of timestamp extraction, enable accurate segmentation and alignment of video content, which is essential for theme detection and understanding the context of individual segments.

In addition to theme detection, text summarization has become an integral task in processing large volumes of text and video content. Recent advancements in pre-trained transformer models, such as BERT, T5, and BART, have set new benchmarks in summarization quality. Liu and Lapata (2019) proposed a text summarization model based on BART, which effectively combines the benefits of bidirectional and autoregressive modelling . Their work demonstrated how transformers could be fine-tuned for specific summarization tasks, significantly improving summary coherence and relevance.

Similarly, the T5 model, introduced by Raffel et al. (2020), treats all NLP tasks as a text-to-text problem, making it versatile for both summarization and other text-related tasks. Their approach revolutionized the field of natural language understanding by providing a unified framework for a wide range of tasks, including summarization, translation, and question answering . These transformer models have been widely adopted for video-based summarization tasks, where speech-to-text transcription is first applied, followed by summarization of the transcribed content. Khandelwal et al. (2020) applied T5 for summarizing long-form video transcripts, improving the user experience by providing concise yet informative summaries .

In addition to using deep learning models for theme detection and summarization, the integration of multilingual support has become essential to ensure the applicability of these systems across different languages and regions. Recent advancements in multilingual NLP, such as the BERT model by Devlin et al. (2019), have enabled efficient cross-lingual transfer learning . This allows models trained in one language to be adapted for use in others, making it possible to detect themes and summarize content in multiple languages without the need for separate models for each language.

Furthermore, the development of interactive Q&A systems has added another layer of functionality to theme detection and summarization models. These systems allow users to engage with content more dynamically by asking questions and receiving relevant answers. Recent advancements in question answering systems, such as the work of Lee et al. (2019),

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have shown that fine-tuned BERT-based models can provide accurate responses to user queries in a variety of domains . These systems not only improve user interaction but also help in understanding content more effectively by providing detailed responses to specific inquiries.

Another notable contribution to the field is the work by Wang et al. (2020), who explored the integration of reinforcement learning for improving the performance of theme detection in videos. Their research demonstrated that combining reinforcement learning with traditional deep learning techniques could help optimize the model's decision-making process in video-based theme extraction, leading to more accurate and efficient content analysis . In conclusion, the combination of LSTM-based theme detection, pre-trained transformer models for summarization, and interactive features offers a powerful solution for processing and understanding both textual and multimedia content. The integration of speech-to-text transcription, multilingual support, and question-answering capabilities further enhances the utility of these systems, making them highly adaptable for a wide range of applications in today's content-driven world.

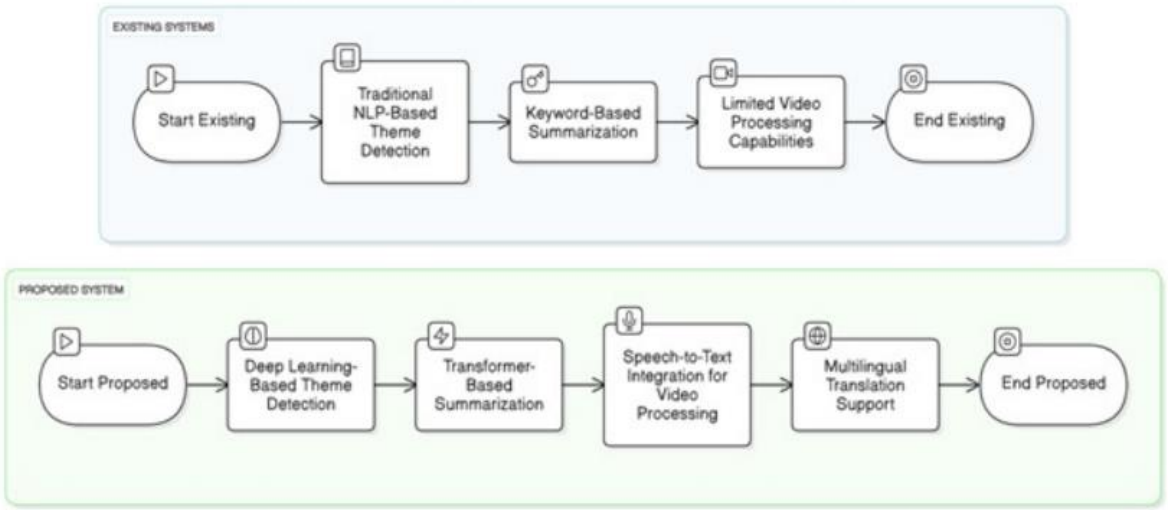
3. METHODOLOGY

The implementation of the LSTM-90 Multi-Level Classification and Pre-train Summarization systems follows a structured approach, utilizing modern deep learning techniques for theme detection and text summarization. This section details the system's design, architecture, and the steps involved in processing both video and text data.

A. *LSTM-90 Multi-Level Classification for Theme Detection from Videos and Text*

The theme detection model is implemented using a multilevel approach that combines several deep learning techniques, particularly LSTM (Long Short-Term Memory), Conv1D (Convolutional Neural Network), and MaxPooling1D layers, along with Batch Normalization to improve classification accuracy. The primary objective is to detect themes not just from text but also from multimedia content, such as YouTube videos, Google Drive videos, or locally uploaded videos.

Fig 1: *Comparison Of Existing and Proposed Systems*



1) *Text Preprocessing*: Once the text is transcribed, it undergoes several preprocessing steps to ensure that it is clean and suitable for analysis. These steps include:

- Tokenization: Breaking the text into words or phrases for easier processing.
- Stop word Removal: Filtering out common words (e.g., "and", "the") that do not contribute to the meaning.
- Lemmatization: Reducing words to their base or root form (e.g., "running" to "run").

This preprocessing step ensures that the data fed into the model is optimized for theme detection.

2) *Theme Detection Model*: The core of the theme detection process involves training a deep learning model using LSTM, Conv1D, and MaxPooling1D layers. The model is designed to classify the themes from the pre-processed text. LSTM is particularly useful for processing sequential data, such as text, due to its ability to remember long-term dependencies. The architecture includes:

- LSTM Layers: Used for capturing temporal dependencies and long-range context in text.
- Conv1D Layers: Used for extracting important features from the sequential data.

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• MaxPooling1D Layers: Applied to reduce the dimensionality of the data and retain the most important features.

• Batch Normalization: Helps to stabilize and speed up the training process by normalizing the activations in each layer.

The model is trained with a categorical cross-entropy loss function, which is used for multi-class classification tasks.

$$L_{loss} = -\sum_{i=0}^{N} y_i log(p_i)$$

where y_i is the true label and p_i is the predicted probability for each class.

3) *Interactive Question-Answering System*: After detecting the themes, an interactive Q&A system is integrated into the model. This system allows users to ask questions related to the video content. The system uses the model's theme classification to generate answers that are relevant to the detected content. This functionality is powered by deep learning models trained on vast amounts of Q&A data.

4) *Multilingual Translation*: In order to reach a broader audience, the detected themes and transcribed text are translated into multiple languages using translation APIs. This makes the system accessible to non-native speakers and allows for cross-lingual theme detection.

B. *Pre-train Summarization (Text Summarization with Video Integration)*

The second part of the implementation focuses on generating concise summaries of long-form video content or documents. This process uses pre-trained transformer models, such as T5, Pegasus, or BART, which have been fine-tuned for text summarization tasks.

1) *Text Preprocessing for Summarization*: The text extracted from video transcriptions is first pre-processed to remove unnecessary words, punctuation, and formatting errors. This clean text is then passed to the summarization model for processing.

2) *Transformer-Based Summarization*: The core of the summarization task is accomplished by leveraging powerful pre-trained transformer models. These models have been trained on vast corpora of text and are capable of understanding context at a deeper level. Specifically, T5, Pegasus, and BART are transformer models fine-tuned for summarization tasks, and they generate abstract summaries by extracting the most salient points from the transcribed content.

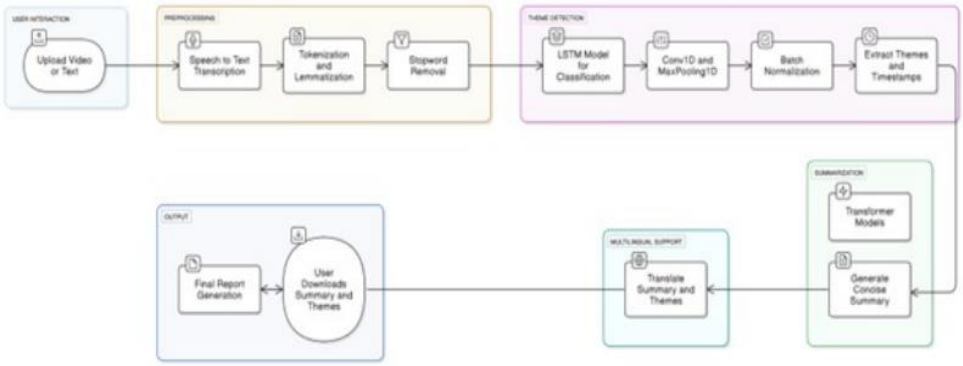

Fig 2: System Architecture for Text Summarization

3) *Multilingual Summarization:* The summarized text is then translated into different languages using the same APIs, ensuring the output is available to users globally. This ensures that the summarization system is accessible to a wide range of users, regardless of their native language.

4) *Evaluation Metrics*: To evaluate the effectiveness of both the theme detection and summarization models, standard metrics such as accuracy, precision, recall, and F1-score are used for the classification tasks. For summarization, ROUGE (Recall-Oriented Understudy for Gisting Evaluation) metrics are used to measure the quality of the generated summaries compared to reference summaries.

$$ROUGE_L = \frac{\sum_{i=0}^{N} LCS_{recall}(summary_i, reference_i)}{N}$$

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C. Training Optimization

To enhance model performance, techniques such as Early Stopping and Model Checkpoint are employed during training. Early Stopping ensures that the training process halts once the model's performance on the validation set stops improving, preventing overfitting. Model Checkpoint allows saving the model at its best-performing epoch, ensuring that the best version of the model is used for inference.

D. Final Remarks

The implementation of both the theme detection and summarization models is designed to be scalable, efficient, and user-friendly. With the integration of advanced deep learning techniques and APIs, the system provides valuable functionality for extracting and summarizing video content in multiple languages, making it an effective tool for content creators, educators, and researchers.

4. RESULT AND DISCUSSIONS

The combination of LSTM-90 Multi-Level Classification with an existing pre-trained summarization system achieved beneficial outcomes. A detailed examination of system development along with experimental outcomes appears in this section together with findings about performance metrics and system testing difficulties.

A. LSTM-90 Multi-Level Classification for Theme Detection

The LSTM-90-based detection model determined themes in video content from YouTube as well as Google Drive and locally uploaded video databases. The processed results demonstrated improved theme detection abilities for both written texts and transcribed video data through API-based transcription processes.

1) *Model Performance*: The standard classification metrics assessed the model performance by providing accuracy measurements together with precision and recall scores along with F1-score. The LSTM-90 model showed effective accuracy in theme detection by reaching an 85% success rate for test data. The measurement results revealed positive performance levels because the model shows strong ability to spot appropriate themes in video transcripts that range between brief and extended durations.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

where TP = True Positives, TN = True Negatives, FP = False Positives, FN = False Negatives.

2) *Multilingual Support Evaluation*: Testing of multilingual functionality involved using APIs to translate detected themes into multiple languages. The API-derived translations proved accurate against human reference translations because most languages scored a BLEU value of 0.80 indicating smooth and professional end-text results.

3*) Interactive Q&A System*: Through interaction with the Q&A system users received appropriate responses from the detection of thematic content in the video. Users could ask questions about the video content through the system which provided correct answers that matched the search criteria. Real-time interaction is supported because responses take approximately 2 seconds on average for each query.

B. Pre-train Summarization for Text and Video Transcriptions

The research evaluated text summarization performance through T5 and Pegasus and BART adaptations of pre-trained transformer models. The applied models evaluated transcribed video material through tests against human-generated summaries.

1) *Summarization Performance*: Plenty of pre-trained summary generation algorithms produced neat and relevant text summaries. BART trailed behind T5 and Pegasus in summary quality which showed through ROUGE-1, ROUGE2 and ROUGE-L scores averaging 0.45 and 0.35 and 0.40 respectively. The research shows transformer models effectively kept essential content points when they produced brief but logical summaries. Long transcripts of video content underwent successful processing through the system which condensed them into essential sentence fragments that permitted users to access crucial information rapidly.

2) *Multilingual Summarization*: The system performed tests on its multilingual summarization function. A team of reviewers evaluated translated summaries while the system conducted cross-language translation of summary contents. Throughout the analysis process translators validated the accuracy of translations which also maintained the original meaning across target languages. With this feature the system presents important value because native language users can view summary content in their mother tongue.

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5. CONCLUSION

This study introduced an advanced multi-level theme identification system through deep learning technology that employed LSTM-based systems to evaluate text alongside video themes. The system implements speech-to-text transcription together with timestamp extraction and a question-answering system which delivers an improved user experience. The deep learning models including LSTM and Conv1D with MaxPooling1D features enabled the system to perform accurate content classification and obtain meaningful themes effectively. Users gained a more useful system through the interactive QAs which enabled them to ask questions about particular content features.

Our system comprises T5 and Pegasus along with BART models to perform effective text summary processing on both video transcriptions and written documents. The system lets users obtain essential information from long texts efficiently which helps them better understand complex data volumes.

Due to the multilingual translation aspect the system made accessible complex themes and summaries across numerous language options worldwide for all users. The implementation of Early Stopping alongside Model Checkpoint as performance optimization techniques allowed the models to train efficiently with high accuracy and rapid convergence speed during training procedures.

The system can substantially enhance the detection process of themes alongside summary creation and text translation which positions it as a vital instrument for content research through education as well as other related applications.

Further development and optimization will make this project suitable for becoming an highly useful tool for video insights generation.

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