Comparative Analysis on Intelligent Classification of Misinformation Based Data in Social Media Content

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Abstract: *Online social networks facilitate the rapid and extensive dissemination of messages and news. The rapid dissemination of legitimate news and messages is commendable; however, the swift spread of misinformation raises concerns regarding the reliability and trustworthiness of these networks. Consequently, the detection of misinformation and the mitigation of its dissemination have emerged as significant subjects within social network analysis. The increase of misinformation on social media has significant societal and cultural implications, highlighting the need for effective detection systems. This paper analyzes uni-modal and multi-modal misinformation classification systems, utilizing Artificial Intelligence (AI) to address the challenge. Also, uni-modal (text-only, image-only) and multi-modal (text-image, video) approaches are analyzed for the classification of misinformation. This paper evaluates the effectiveness of various modalities using advanced AI models and discusses the challenges and opportunities in designing robust misinformation detection systems. Experimental results indicate that multi-modal systems surpass uni-modal models in the detection of complex misinformation, highlighting the necessity for comprehensive frameworks in addressing digital falsehoods.*

Keywords: Artificial Intelligence, Social Media Content, Misinformation Classification, Multimodal Data, Machine Learning.

I. Introduction

Social media has transformed communication by facilitating the swift dissemination of information to extensive audiences. Platforms like Twitter, Facebook, Instagram, and TikTok serve as essential channels for news dissemination, public discourse, and marketing. Nonetheless, the democratization of information presents considerable challenges, with the proliferation of misinformation being one of the most critical issues. Misinformation is characterized as false or misleading content disseminated without malicious intent. It can transition into disinformation when shared with the explicit intention to deceive. The phenomena have significant consequences, such as diminishing public trust, impacting elections, and worsening public health crises. Disinformation can be regarded as a natural phenomenon within social operations [2]. It is often used to describe tales that have gained a lot of attention online but have not been confirmed or explained by reliable sources. Many researchers have run across this issue; it's not limited to the social sciences, media, and computer science. Misinformation disseminates swiftly on social media platforms due to advancements in Internet technology, characterized by fission-like spread, rapid propagation, extensive reach, and significant impact. Many people's physical and mental well-being are jeopardized because of the widespread dissemination of misinformation and falsehoods on social media, which poses serious challenges to governments and social order [3-5].

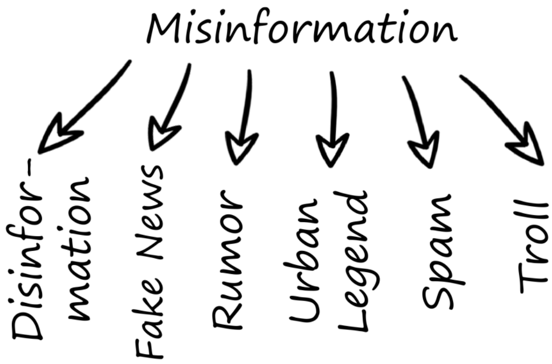

Figure 1: Essential terminology pertaining to misinformation [1].

Misinformation, comprising spam, rumors, and fake news, has proliferated rapidly due to the accessibility and immediacy of social media platforms. Recent instances of disinformation highlight the urgent need to develop methods for identifying false information. Journalists have analyzed the mechanisms of disinformation propagation; The intrinsic accessibility of digital platforms, along with the capacity for automation, enables the fast dissemination of misinformation to large audiences, hence posing new issues. Misinformation refers to false or inaccurate information that has been intentionally or unintentionally disseminated [18]. Figure 1 illustrates that several phrases exhibit conceptual similarities, making them susceptible to misunderstanding. For example, fake news is news that is made up, but it's not always disinformation because it can be shared by innocent users. A rumor is information that hasn't been checked out and may or may not be true, and spam is information that is sent to a lot of people that isn't relevant [25–26]. The complexity of misinformation is heightened by the diverse modalities it utilizes, such as text, images, videos, and their combinations (multi-modal content). Misinformation in text form can encompass fabricated news articles or deceptive captions, whereas images and videos are employed to distort or misrepresent events. Multi-modal misinformation, exemplified by memes that integrate text with altered images, poses distinct challenges arising from the interaction between modalities [37-38]. Addressing misinformation necessitates a comprehensive approach that can analyze and classify various content types. This paper examines artificial intelligence methods for identifying misinformation in both uni-modal and multi-modal social media data, and evaluates the effectiveness of these approaches in comparison to one another.

The rest of the paper is structured into eight sections. The challenges encountered in the classification of misinformation addressed in section 2. Section 3 addresses the role of AI in the detection of misinformation. Section 4 examines the relevant literature concerning unimodal and multimodal models. Section 5 presents the benchmark dataset acquired throughout the analysis. Section 6 provided an overview of the generic methodologies. Section 7 presents the comparative results from the experiments along with a discussion. Finally, a paper conclusion was given.

II. Challenges In Misinformation Detection

The identification of disinformation constitutes a multifaceted and evolving task. This paper outlines significant challenges encountered in the detection of misinformation across various digital ecosystems and social media platforms [2][4]:

- *Data Availability and Quality:* There is a scarcity of high-quality, labelled datasets for the detection of misinformation, particularly concerning less prevalent languages and regions. Misinformation datasets frequently exhibit a higher prevalence of truthful information compared to falsehoods, resulting in bias during model training.
- *Multi-Modal Complexity:* Misinformation frequently manifests in textual, visual, or audiovisual formats. The integration of multi-modal data enhances computational and algorithmic complexity. Misinformation adapts to trends, cultural changes, and new subjects, rendering historical data inadequate for training purposes.

- *Multilingual and Cross-Cultural Misinformation:* Unfortunately, detection models frequently struggle with languages with little resources or those that do not fully grasp cultural context, both of which contribute to the widespread dissemination of misinformation.
- *Changing Definitions of Misinformation:* Misinformation is context-dependent and influenced by cultural and temporal factors. What is considered true or false at present may evolve over time, particularly with the advent of new scientific knowledge.

III. Role Of Artificial Intelligence (AI) In Misinformation Classification

Artificial Intelligence (AI) is essential in tackling the intricate and escalating issue of misinformation on digital platforms. AI improves the identification, categorization, and mitigation of misleading or erroneous information by utilizing its enhanced capabilities. Artificial intelligence has developed into an effective tool for the detection of misinformation, providing enhanced abilities in feature extraction, pattern recognition, and classification [5-7]. Methods that rely on artificial intelligence make use of ML and DL models to:

- Identify linguistic patterns in text via Natural Language Processing (NLP) approaches that extract elements such as mood, tone, and semantic errors in textual material.
- Identify manipulated or misleading visuals using Computer Vision models that detect manipulated images, deepfakes, and misleading visuals.
- Analyse multi-modal content by integrating features from multiple modalities which combines information from modalities (e.g., text, images, audio or video) for holistic classification.

Multi-modal systems integrate data from many modalities to enhance classification accuracy, in contrast to uni-modal techniques that only analyse one modality, such text or pictures. The capacity of AI systems to combat disinformation in both multi-modal and uni-modal systems has been substantially improved by recent developments in DL models.

IV. Literature Review

The identification of misinformation on social media has received considerable scholarly focus owing to its societal consequences. This section presents a thorough review of current research in uni-modal and multi-modal misinformation classification, emphasizing methodologies, significant findings, and limitations.

1. Uni-modal Systems

Uni-modal systems concentrate on the analysis of a singular modality, such as text. These systems are prevalent because of their simplicity and reduced computational demands. An evaluation of AI models conducted to combat the spread of health-related disinformation on social media platforms during the COVID-19 epidemic [11]. The effectiveness of three machine learning algorithms in differentiating between fake news and authentic articles was assessed [12]. The propagation of false information about COVID-19 on social media performed using ensemble methodologies [13]. Fake news is classified utilizing the probabilistic latent semantic analysis method [14]. A-KWGCN-based model presented for detecting false news stories using knowledge-and weighted graph convolutional networks (GCN) [15]. The accuracy of detecting false news is enhanced by ML models tactics that focus on feature engineering which involve manipulating and extracting significant qualities from raw data [17]. The classification of COVID-19-related news is based on data aggregated from various social media and news sources [21]. Various approaches have been compared including traditional ML and DL methods [22]. FakeBERT model proposed which combines BERT with many concurrent blocks of a deep Convolutional Neural Network (CNN) with different kernel sizes and filters [30]. A prototype for automating the early detection of false news presented using supervised ML models with count-vectorizer and tf-idf feature extractor [32]. The dissemination and identification methods of misinformation on Social Networking Sites (SNSs), including harmful social and software agents, are examined [34]. Fake news detected which are collected from Facebook using advanced ML models [35]. Misleading information has been identified on Twitter, along with potential strategies that the social media platform could implement to mitigate the dissemination of misinformation [36].

2. Multi-modal Systems

Multi-modal systems combine various modalities, including text and images, to enhance classification accuracy. These systems overcome the limitations of uni-modal approaches by utilizing complementary information from various modalities. MPFN model presented to record the representational information of each modality at distinct levels [8]. The importance of the innovative fine-grained and multimodality classification particular to Fakeddit was highlighted by comprehensive tests that assessed hybrid text and picture models across multiple categorization variants. [9]. A novel logic-based neural model has been proposed that integrates interpretable logic clauses to articulate the reasoning process of the target task [10]. Detection of false news presented using MetaFEND model using a small number of confirmed postings about emerging events [16]. DL based model used to analyze emotions and content to detect the fake information based on properties of their network diffusion [18]. To achieve high classification accuracy with each learner focusing on separate chunks of news information, a new loss function presented [19]. Two-branch technique learned hidden layer information from both modalities to extract more informative characteristics, allowing for the identification of fake news by combining visual and textual data [20]. The multimodal approach proposed which integrates text and image data using CNN architecture, yields superior performance when compared to the unimodal approach for fine-grained categorization [23]. Using supplementary characteristics in addition to the textual content of tweets, a novel hybrid approach presented to detect false news by using COVID-twitter-BERT language model, which is pre-trained, to encode the meaning of tweets into a dense representation [24]. An analysis was conducted on tweets containing URL news links from both recognized misinformation sources and credible domains [25]. Multimodal framework utilized an entire-image multimodal model with contrastive learning (TTEC) and BERT-based back-translation text [26]. Text and image based two new multimodal benchmark datasets presented to enhance the efficacy of false news detection [27]. An approach to detecting misleading information that utilizes Text-CNN and SE modules has been suggested [28]. Various architectures have been developed to learn linguistic and visual models from the post independently [29]. Using BERT, a multimodal feature vector with high information content is generated by integrating textual and visual data in an automated system for detecting bogus news [31]. A framework called SAMPLE was created to identify bogus news using multimodal approach, which combines learning [33].

3. Limitations in Existing Work

While there have been notable advancements in AI-driven misinformation detection, current research encounters various limitations, especially regarding the challenges of integrating unimodal and multimodal social media data. Many studies emphasize unimodal approaches, which inadequately address the comprehensive context of misinformation dissemination on social media. Multimodal approaches present potential benefits; however, integrating the text, image, and additional data modalities poses significant technical and computational challenges. Addressing limitations is essential for advancing misinformation detection methods and developing robust, trustworthy AI systems that can effectively manage misinformation dynamic and multimodal characteristics in the digital era.

V. Benchmark Datasets for Misinformation Detection

The availability of high-quality datasets is critical for developing robust misinformation detection models. Key datasets include:

- ***Twitter Dataset [8]:*** This dataset was produced and made public by the MediaEval benchmarking Initiative with the purpose of evaluating multimodal performance which comprises a sequential collection of tweeted images and text, consisting of 5000 true and 6000 rumor posts designated as the train set. The test set included a diverse range of breaking news, comprising up to 2000 posts. Posts that consist solely of images or text are prohibited from participating in the train or test processes.

- ***Weibo Dataset [8]:*** Recent studies have used this microblogging dataset to test multimodal algorithms for detecting fake news; however, these tests have only included Chinese articles or comments.
- ***Fakeddit Dataset [9]****:* As a social news and debate site, Reddit allows users to post material across different subreddits; this is where the dataset was retrieved from. The dataset comprises more than 1 million submissions sourced from 22 distinct subreddits.
- ***LIAR Dataset [17]****:* Open source dataset that can identify fake news by utilizing POLITIFACT.COM, a resource that provides comprehensive analytical reports and actual documentation for each case and extracted 12.8K hand-labeled short statements spanning many contexts and years.
- ***FakeNewsNet Dataset [22]****:* A multi-modal dataset that incorporates both visual and textual forms of disinformation. Information on news stories, their social context, and their location and time are all part of two datasets that make up this multi-dimensional data repository.

VI. Framework for Misinformation Classification Using AI

The methodology emphasizes the design and implementation of both uni-modal and multi-modal systems for classifying misinformation, utilizing Artificial Intelligence (AI). The process includes dataset preprocessing, feature extraction, model selection, training, and evaluation. The subsequent sections present a comprehensive, sequential outline of the process.

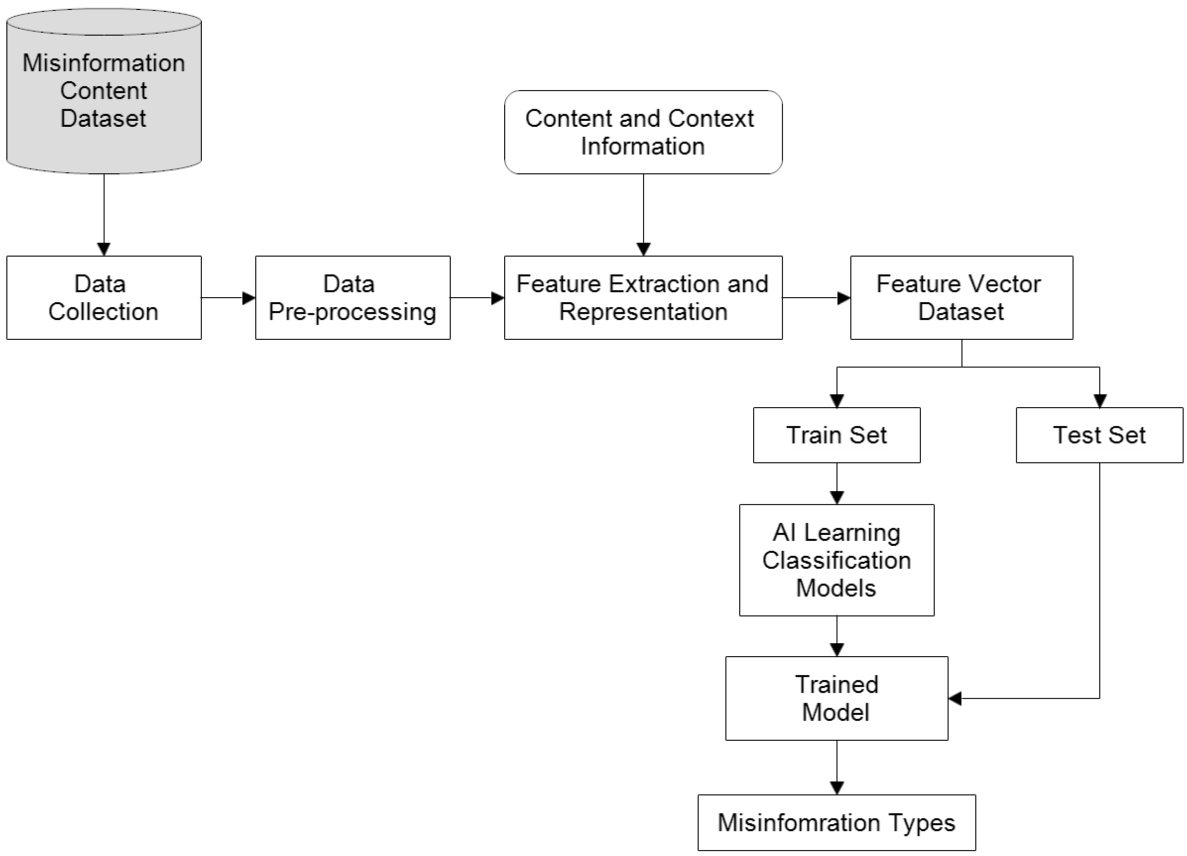

Figure 2: Generic Framework for Misinformation Classification

1. Data Collection

Unimodal data encompasses various forms that include text, including captions, social media postings, news articles, and tweets; visual data comprising images like memes, doctored images, and infographics; and audio/video data, which includes speeches, podcasts, and video content. Multimodal data encompasses a combination of text, images, audio, and video. Examples consist of social media posts featuring text alongside images, or videos that include captions and audio.

2. Data Preprocessing

Data preprocessing is an essential phase in AI model development, as it guarantees that the input data is clean, standardized, and appropriate for the intended task. Data cleaning for text involves the elimination of irrelevant or noisy information. Missing values are substituted with the mean of all samples. Normalization and tokenization have been implemented. Image data undergoes resizing, cleaning, normalization, and augmentation operations. Audio cleaning is conducted using sample segmentation for audio data.

3. Feature Extraction

Feature extraction involves converting raw data into a collection of significant and informative attributes (features) suitable for input into machine learning models. The methodology is contingent upon the data modality, such as text, image, audio, or multimodal formats. Tokenization and word embedding processes utilize techniques such as Word2Vec, GloVe, and BERT for text data analysis. Image data features are extracted utilizing CNNs or pre-trained models. Pretrained models are utilized for audio data through audio spectrograms or embeddings.

4. AI Learning Classification Models

Classification modelling in AI entails the development of ML or DL models designed to allocate input data to established categories or classes. Classification can be categorized into two types: Binary and Multi-class. Classification. News articles are categorized into politics, sports, and technology. Traditional ML models employ supervised techniques such as Support Vector Machines (SVM), Naive Bayes (NB), Random Forest (RF), and Decision Trees (DT). Advanced approaches in DL models include CNN, recurrent neural networks (RNN), Long Short-Term Memory (LSTM) Networks, and Transformer-based models.

5. Evaluation Metrics

Misinformation is categorized using a variety of performance criteria. The most common measures used for each modality are F1-score, Accuracy, Precision, and Recall.

VII. Comparative Result Analysis

A comprehensive evaluation of the experimental results obtained from the use of multi-modal and uni-modal misinformation categorization systems is presented in the results and discussion section. Accuracy, F1-score, recall, and precision are some of the performance indicators used for assessment. Table 1 compares and contrasts uni-modal methods, whereas Table 2 does the same for multi-modal techniques.

Table 1: Comparative Result Evaluation for Unimodal Systems

Reference	Modality	Dataset	Methodology	Evaluation Metrics
M Sikosana et.al. [11]	Text	COVID19-FNIR DATASET	CNN+LSTM	Accuracy – 0.9921, F1score – 0.9917, Recall – 0.985, Precision – 0.998.
G Airlangga et.al. [12]	Text	Real Time Data Samples	TF-IDF + Passive Aggressive Classifier	Accuracy – 0.99, F1score – 0.99, Recall – 0.99, Precision – 0.99.
J Naeem et.al. [13]	Text	Youtube Comments for COVID-19	ML Models	Accuracy – 0.94, F1score – 0.78, Recall – 0.93, Precision – 0.94.
S Mishra et.al. [14]	Text	Fake News	GAN	Accuracy – 0.90, F1score – 0.88, Recall – 0.88, Precision – 0.88.
L Fu et.al. [15]	Text	Twitter15 and Twitter16	A-KWGCN	Accuracy – 0.90, F1score – 0.89, Recall – 0.88, Precision – 0.89.
G Parthiban et.al. [17]	Text	LIAR	CNN	Accuracy – 0.87, F1score – 0.89, Recall – 0.87, Precision – 0.88.
S Khan et.al. [21]	Text	COVID-19 fake news	Random Forest	Accuracy – 0.88, F1score – 0.88, Recall – 0.89, Precision – 0.87.
W Han et.al. [22]	Text	Fake News	LSTM-CNN	Accuracy – 0.80, F1score – 0.39, Recall – 0.39, Precision – 0.43.
R K Kaliyar et.al. [30]	Text	Real-world Fake News	FakeBERT	Accuracy – 0.98

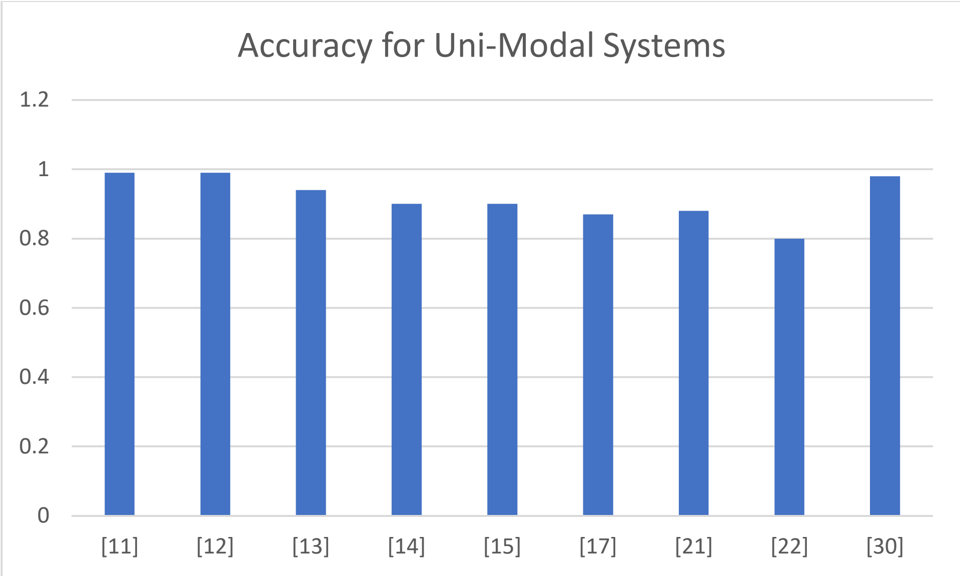

Figure 3: Accuracy Evaluation for Uni-modal systems

Table 2: Comparative Result Evaluation for Multi-modal Systems

Reference	Modality	Dataset	Methodology	Evaluation Metrics
J Jing et.al. [8]	Text, Image	Twitter, Weibo	MPFN Model	Accuracy – 0.838, F1 – 0.889, Recall – 0.894, Precision – 0.857.
K Nakamura et.al. [9]	Text, Image	Fakeddit	BERT-ResNet50	Accuracy – 0.8909
H Liu et.al. [10]	Text, Image	Twitter, Weibo	LogicDM	Accuracy – 0.911, F1score – 0.859, Recall – 0.816, Precision – 0.909.
H Liu et.al. [10]	Text, Image	Sarcasm	LogicDM	Accuracy – 0.881, F1score – 0.853, Recall – 0.850, Precision – 0.857.
Y Wang et.al. [16]	Text, Image	Twitter, Weibo	MetaFEND	Accuracy – 0.88, F1score – 0.88
G Parthiban et.al. [17]	Text	LIAR	CNN	Accuracy – 0.87, F1score – 0.89, Recall – 0.87, Precision – 0.88.
A A Obaid [19]	Text, Image	Politi-Fact, Gossip	Ensemble of Deep Learners based on Attention Mechanisms	Accuracy – 0.85, F1score – 0.76, Recall – 0.82, Precision – 0.70.
Y Guo et.al. [20]	Text, Image	Twitter, Weibo	Multimodal Bilinear Pooling and Attention Mechanism	Accuracy – 0.90, F1score – 0.90, Recall – 0.87, Precision – 0.94.

I S Bedmar et.al. [23]	Text, Image	Fakeddit	Multimodal CNN	Accuracy – 0.87, F1score – 0.87, Recall – 0.86, Precision – 0.88.
R A Dar et.al. [24]	Text, Contextual Information	ECTF COVID-19 Fake News	Ensemble Deep Model	Accuracy – 0.98, F1score – 0.98, Recall – 0.98, Precision – 0.98.
S Jindal et.al. [27]	Text, Image	NewsBag, NewsBag++	Multimodal Variational AutoEncoder	Accuracy – 0.71.
Y Lang et.al. [28]	Text, Image	Twitter, Weibo	Text-CNN and SE	Accuracy – 0.90, F1score – 0.92.
S K Uppada et.al. [29]	Text, Image	Fakeddit	Xception	Accuracy – 0.82
B Palani et.al. [31]	Text, Image	Politifact, Gossipcop	CB-Fake	Accuracy – 0.93

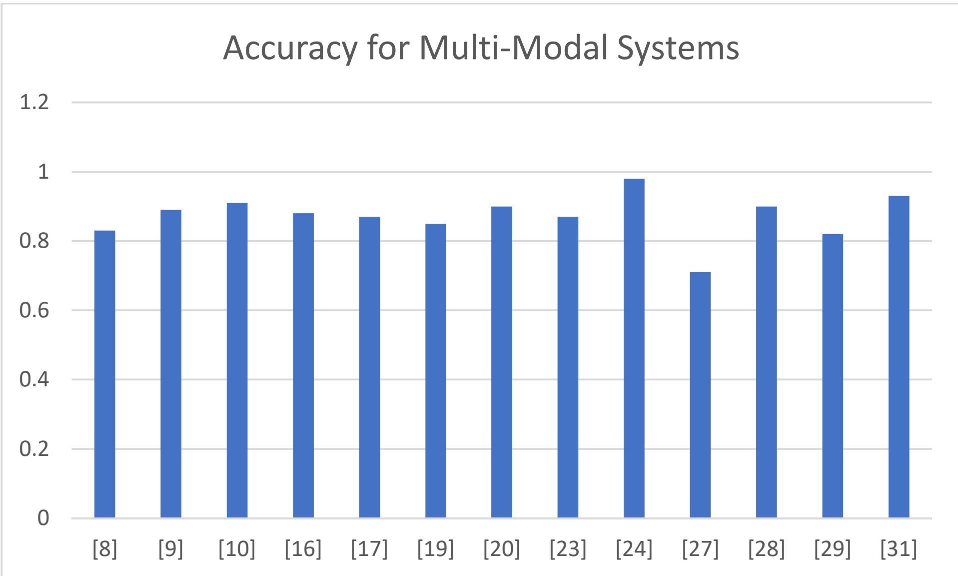

Figure 4: Accuracy Evaluation for Multi-modal Systems

Figures 3 and 4 show that, since text and visual characteristics complement each other, multi-modal approaches often beat uni-modal solutions. The integration of textual and visual modalities overcomes the constraints of uni-modal systems, resulting in enhanced accuracy and robustness. Attention mechanisms in hybrid fusion models enhance the system's capacity to concentrate on pertinent modalities for classification. The hybrid multi-modal system demonstrates scalability for real-time applications through the utilization of distributed computing or cloud platforms. Effective utilization of social media platforms can aid in addressing misinformation and mitigating its societal and political consequences.

VIII. Conclusion

This paper explored the incorporation of AI methods in the detection of misinformation, emphasizing a comparative analysis of unimodal and multimodal strategies utilized on social media data. The misinformation classification framework utilized advanced AI learning architectures to effectively process and classify various data types, such as text, images, and their combinations. The findings revealed that multimodal models significantly outperformed unimodal counterparts, highlighting the importance of integrating complementary features from multiple modalities to enhance classification accuracy and robustness. Nonetheless, the study recognized limitations, including dependence on labelled multimodal datasets and difficulties in handling low-resource languages and noisy real-world data. The identified constraints highlight the necessity for future research to focus on dataset diversity, investigate transfer learning methods applicable to low-resource contexts, and improve scalability across various platforms.

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