MULTI-MODALLEARNING FOR DETECTING RUMORSONSOCIAL MEDIA

#1 J.KUMARI, #2 Y.SUDARSHANBABU
1 ASSISTANT PROFESSOR # 2 MCA SCHOLAR
DEPARTMENTOFMASTEROFCOMPUTERAPPLICATIONS
QIS COLLEGE OF ENGINEERING AND TECHNOLOGY
VENGAMUKKAPALEM(V),ONGOLE,PRAKASAMDIST.,ANDHRAPRADESH- 523272

ABSTRACT

Theswift advancement ofsocialmediaplatforms and theexpanding volumeofsocialmediadata have rendered the task of rumor detection crucial, as the veracity of posts cannot be assured. Numerous methodologies have been introduced to enhance the rumor detection process through the applicationofmulti-task learning, whichseeks to augment the efficacyofrumor detectionby capitalizing on the pertinent information derived from stance detection. Nevertheless, the prevailing methodologies exhibit three primary limitations: (1) they predominantly concentrate on textual content while disregarding the crucial multi-modal information inherent in social media data; (2) they overlook the disparities in feature space between the stance detection and rumor detection tasks, leading to suboptimal utilization of stance information; (3) they significantlyoverlookthe semantic informationembedded withinthe nuanced stance labels. This research presents a Multi-modal Meta Multi-job Learning (MM-MTL) framework for the job of detecting rumors on social media. We develop a multi-modal post embedding layer that integratesbothtextualand visualcontent. To addressthe featuresharing issue instance detection and rumor detection tasks, we present a Meta knowledge-sharing framework that facilitates the sharing of higher meta network layers to extract the underlying meta information from multi-modal posts. To optimize the semantic information embedded in the detailed attitude labels, we implement the attention method to assess the significance of each reply. Comprehensive studies on two Twitter benchmark datasets indicate that our suggested technique attains state-of-the-art performance.

I.INTRODUCTION

Online social media platforms haveemerged as the paramount channel for individuals to disseminate, organize, and propagate information. In contrast to traditional media, where news is disseminated by respected institutions, internet news on social media platforms is spontaneously released and shared by hundreds of millions ofusers. Nevertheless, a limited number of users meticulously verify the veracity of the material they disseminate, resulting in the proliferationof numerous rumors. The lack ofa precise and methodical approach to verifying posts can lead to widespread adverse consequences from the spread of social media rumors, potentially influencing or manipulating significant public events. Consequently, efficiently detecting misinformation and mitigating its adverse effects has emergedas a substantial problem for social media platforms. Numerous initiatives have been undertaken to mitigate the detrimental impacts of rumors. The initial endeavors originate from news websites like snopes.com and politifact.com, which aimto elucidate or validate rumors by expert research and crowd sourcing. Nevertheless, the manual collection and examination of rumorsisexceedinglytime-consumingand inherently inefficient. Consequently, the automatic mining and detection of rumors has garnered significant interest within the scholarly community. Existing research on automatic rumor identification can be categorized into two distinct groups: The initial category involves the extraction or construction of intricate and extensive features by manual methods. Castillo et al. create numerous handcrafted characteristics from the media content of postings and the social context of users, then employing these features to train a support vector machine. The second category is the automatic extraction of deep features via neural networks. Ma et al. offer a recurrent neural network designed to extract hidden representations from the textual content of pertinent messages. Yu et al. employ a convolutional neural network to extract essential elements and their high-level interactions from the textual content of the claims. While these algorithms demonstrate encouraging efficacy in rumor identification, the majority of these approaches predominantly concentrate on textualcontent. The content of social media posts may encompass several modalities (e.g., text, photos), and these diverse modalitiescanenhanceoneanother.

Furthermore, the tweets in rumor identification tasks are exclusively authored by users, and the user's viewpoint significantly influences rumor detection. Consequently, it is essential to utilize multimedia content and the user's perspective for rumor identification. A recent multi-task learning method has been presented to include users' stance information into the rumor detection job.Ma et al. introduce an innovative shared-private multi-task learning approach to enhance information sharing and representation reinforcement between the stance detection and rumor detection tasks, thereby augmenting valuable features for each task. Doubtful and opposing voices frequently emerge alongside the dissemination of rumors, serving as useful markersoftheinformation'sveracity. While enhancing social media rumor detection by the identification of rumors and the concurrent analysis of diverse perspectives appears logical, current methodologies remain inadequate in effectively tacklingthe following three issues.

1) Feature-level challenge: The datasets for rumor detection and stance detection tasks are multi-modal. Social media posts may encompassseveralmodalities(e.g.,text, photos), and these diverse modalities can enhance one another. For instance, in the primary post of Table I, The photosincluded and also communicate the significant information. Nevertheless, the majority of methodologies primarily concentrate on the linguistic content of the post.

2) Meta-level challenge: In contrast to conventionalmulti-tasklearningapproaches that involve tasks of a singular type, the rumor detection task and the stance detection task pertain to distinct categories. Table I illustrates that the rumor detection task constitutes a classification problem, whereas the stance detectiontask represents a sequence labeling problem. Their output structures differ significantly between the two tasks. Consequently, the rumor detection job and the stance detection task occupy distinct positions inside the feature space. Nonetheless, current methodologies mechanically implement the genericfeature-sharing multitask learning approach for rumor detection. The commonattributes in the shared layer are uniformlytransmitted to their corresponding tasks, resulting in the inclusion of irrelevant and perhaps detrimental traits across various tasks.

3) Task-level challenge: The Current methodologies generally incorporate stance information from the stance labels into the rumor detection task via back propagation. The semantic information embedded in the detailed attitude labels is predominantly overlooked. Table I indicatesthat the data in the stance detectiontask are annotated at the post level. The detailed tweet-level labels can significantly enhance the efficacy of the rumordetectiontask.Responsesexhibitinga robust supportive or opposing position significantlyinfluencetheaccuracyofrumor predictions. Consequently, postings with varying posture labels must to possess distinct weights to achieve a thorough representation of the sequence for rumor identification. This research introduces a novel multi-task learning approach: Multi-modal Meta Multi-Task Learning (MM-MTL) to address the aforementioned difficulties. The benefits of MMMTL are threefold: We develop a multi-modal post embedding layer that integrates both textual and visual content. To address thechallenges encountered by feature-sharing multi-task learning approaches, wepresent a knowledge-sharingframeworkformulti-task learning. Rather thansharing lower layers to extract common characteristics across tasks, theproposedmetamulti-tasklearning exchangeshigherlevels:ametanetworkthat acquires reciprocal meta-knowledge from diverse tasks. The meta-knowledge is subsequently employed to dynamically generate the parameters of the task-specific models. Consequently, the stance information from the user's responses is successfully incorporated into rumor detection. To optimize the utilization of the semantic information embedded in the detailed stance labels, we implement an attention mechanism to assess the significance of each reply and explicitly incorporate the concealed states from the stance layer in the attention computation. Consequently, the efficacy of rumor detection is significantly enhanced.

We empirically establish that our approach exhibits greater robustness and efficacythan the current state-of-the-art, as evidenced by two public benchmark datasets for rumor detection tasks on Twitter.

II.RELATEDWORKS

1.Multimodal Fusion for Rumor Detection on Social Media.

Author: Jinetal.

Description: This work introduces a multimodal fusion frameworkthat combines textual and visual features for detecting rumorsonsocialmediaplatforms.The method leverages convolutional neural networks for image features and recurrent models for textual features.

Merits:

- Effectivelyutilizesbothtextand images.
- Improvesrumordetectionaccuracy over single-modality approaches.

Demerits:

- Struggleswithincompletemodality scenarios (e.g., missing images)
- Lacksadaptabilitytonewunseen rumor patterns.

2. Multi-Task Learning for Social Media Rumor Verification

Author: Maet al.

Description: The authors propose a multi-task learning framework that jointly trains rumor detection and stance classification tasks. This approach captures the relationship between public stance andrumor credibility.

Merits:

- Joint learning improves performance of both tasks.
- Exploitsinter-taskcorrelationsfor better generalization

Demerits:

- Limited totext-onlyscenarios.
- Performancedependsonhigh-quality stance labels.

3. Dual-ConsistencyMultimodalNetwork for Rumor Detection (KDCN)

Author: Sunetal. (2023)

Description: This state-of-the-art approach introduces a dual-consistency mechanism to capture inconsistencies within and between modalities (text-image). It also addresses missing modality issues through special input tokens.

Merits:

- Handlesmultimodalinconsistencies.
- Robusttomissingdatascenarios.

Demerits:

- Requiresexternalknowledge resources for optimal performance.
- Computationallyintensive dueto dual consistency layers.

4. Curriculum Learningand Fine-Grained Multimodal Fusion (CLFFRD)

Author: Xu et al. (2024)

Description:CLFFRD integrates curriculum learning,arrangingtrainingfromeasyto hard samples,withfine-grained fusionbetweentextentitiesandvisualobjects .It alsousesinter-andintra-modalfeaturealignment.

Merits:

- Structuredlearningimprovesmodel robustness.
- Fine-grainedfusioncapturesdeeper semantic relationships.

Demerits:

- Complexarchitectureincreases training time
- Requiresprecisedifficultyscoring of training samples

5. Meta-Learning Approaches for Rumor Detection

Author: Zhangetal.

Description: This work explores meta-learning techniques for few-shot rumor detection, enabling models to quickly adapt to new or unseen rumor events with limited labeled data.

Merits:

- Efficient inlow-resourcescenarios
- Enhancesmodelgeneralizationto new rumor patterns

Demerits:

- Requires carefultask formulation for meta-training.
- Mayunderperformwithlarge-scale datasets.
- They require high computational power and long training times due to multiple learning phases.
- The model design and optimization process are complex, making implementation challenging.
- Overfitting may occur when trained on a small number of rumor types or domains.

III.SYSTEMANALYSIS

Online social media platforms have become the most important medium for people to share information. Hundreds of millions of users on social platforms create a huge scale of social media data. These social mediadata have great research values and draw much attention in the research community. Various studies are proposed to explore social media, such as social media analysis, social events understanding, the cyber bullying phenomena understanding, multimedia summarization on micro blogs, election prediction, visual concept learning, opinion mining and multimodal data learning. However, many models are suffering the error caused by the misinformation in social media data. To debunk rumors and minimize their harmful effects, many efforts have been made. Existing work regards social media rumor detection as a supervised classification problem. The main concern of thesupervised classification approach is to define effective features for training rumor classifiers. Early methods design plenty of hand-crafted features to debunk rumors. For example, Castillo et al. provided a wide range of features crafted from the post contents, user profiles, and propagation patterns.Insteadofdefiningcomplexfeature sets, data-driven models are proposed to obtain the state-of-the-art detection performance.Forexample,Maetal.propose a recurrent neural network to learn the hidden representations from the text content of claims. Recently, several approaches conduct rumor detection based on the multimedia content. Jin et al. propose a recurrent neural network with an attention mechanism to fuse image and text featuresof the post for rumor detection.Although some good performances have been achieved, existing methods mainly focus on capturing the content features of post, while always ignore the strong connections between the veracity of claim and the stances expressed in responsive posts. However, the stance information expressedbyuserstowardaparticularrumor can be indicative of the veracity. In this work, we introduce a novel multi-modal meta multitask learning method to improve the performance of the rumor detection task by jointly training the related stance detection task. Multi-task learning aims to improve the performance of one task by using other related tasks. Most of the multi-task learning or joint learning models canbe regarded as parameter sharing approaches, where models are trained jointly, and parametersorfeaturesaresharedacross multiple tasks. Multi-task learning has been widely used in the various tasks of natural language processing and achieved excellent results.Forexample,Collobertetal.propose a unified frame work which uses a shred lookup table for input words, and thenjointly train several NLP tasks using convolutional neural networks.Song et al. propose a multi-source multi- task learning scheme to co-regularize the source consistency and the tree-guided task relatedness for user interest inference. In most of these models, multi-task architectures use the shared private schema to share features across tasks, which divides the features of different tasks into privateand shared spaces, and the task-irrelevant features in shared space are used as extra features for various tasks. Recently, several multi-task learning methods are proposed to improve the performance ofrumor detection by jointly train rumor detection task and stance detectiontask. For example, Ma et al. introduce a GRU-based multi-task learning methodthat shares features acrossthe rumor detection task and stance detection task. In this paper, we propose a multi-modal meta multi-task learning method for social media rumor detection. Different from the above multi-task learning methods which share featuresinvarioustasks,ourmodelshares the meta-level knowledge. Specifically, a meta network is proposed to capture the meta-knowledge acrosstasksand controlthe parameters of task-specific networks. Meta learning, also known as “learning to learn”, intends to design models that can learn new skills or adapt to new environments rapidly with a few training examples. There arethree common approaches:

1) Metric-based approaches which learn an efficient distance metric;

2) Model-based approaches, which use recurrent network with external or internal memory to enhance the generalization;

3) Optimization-based approaches which optimize the modelparameters explicitly for fast learning.

DISADVANTAGES

1) Feature level challenge: The data of the rumor detection task and stance detection taskaremulti-modal.Thecontent ofthepost in social media platforms may consist of multiple modalities (e.g., text, images), and these multiple modality information can complement each other.

2) Meta level challenge: Unlike the generic multi-tasklearningmethodswhichconsistof taskswithonlyonetype,therumor detection task and the stance detection task belong to different categories.

3) Tasklevelchallenge:Existingapproaches typically introduce the stance information in the stance labels into the rumor detection taskthroughthebackpropagation.However, the semantic information hidden in the fine grained stance labels is largely ignored.

PROPOSEDSYSTEM

In this paper, we aim to tackle the above issues by introducing a novel multi-task learning method: Multi-modal Meta Multi-Task Learning (MM-MTL). The advantages of MMMTL are three-folds:

(1) To make use of multiple modalities, we design a multi-modal post embedding layer which considers both textual and visual content.

(2) To overcome the problem faced by feature-sharing multi-task learning methods, we propose aknowledge-sharing scheme for multi-task learning. Instead of sharing some lower layers to extract common features across tasks, the proposed meta multi-task learning shares some higher layers: meta network, which learns mutual meta-knowledge from various tasks. The meta-knowledge is then used to dynamically generatetheparametersofthetaskspecific

models. Thus, the stance information of user's replies is effectively introduced into the rumor detection.

(3) To better exploit the semantic informationhiddeninthefinegrainedstance labels,weemployanattentionmechanismto estimate the weight of each reply and explicitly include the hidden states from the stance layer in the attention calculation. Therefore, the rumor detection performance is further boosted.

Extensive experiments on two Twitter benchmark datasets demonstrate that our rumor detection model outperforms thestate-of-the-art methods.

The main contributions of our paper are summarized as follows:

We propose a multi-modal meta multi-task learning method for social media rumor detection. Different from the generic multi-task learning methods which share lower common features, the proposed method shares the higher meta-knowledge from rumor detection and stance tasks. With the guide of meta-knowledge, the task-specific model can obtain a precise multi-modal representation of every post. We apply an attention mechanism to the multi-modalmeta multi-task learning to fully utilize the stanceinformationofuserreplies.Withthe weighted user responses, the performance of the proposed multi-modal meta multitask learning can be further boosted. We experimentally demonstrate that our modelis more robust and effective than state-of- the-art based on two public benchmark datasets for rumor detection tasks onTwitter.

ADVANTAGES

1. Multi-modal Post Embedding Layer: For each post in the claim, we model its multi-modal content as embedding vectors. Specifically, we employ BERT to generate the embedding vector for the text contentand use VGG19 to obtain the visual embedding for the visual content.

2. Meta Multi-task Layers: We propose a meta multi-task learning method for social media rumor detection, in which a shared meta layer is used to learn the meta knowledge from rumor detection and stance detection tasks. With the guide ofthe shared meta network, the task-specific layer can obtain a precise representation of each post.

3.Task-specific Output Layer: We apply an attention mechanism to the task-specific output layer to fully utilize the stance information ofthe user replies. In particular, therplieswiththestrongsupportordenial

Stance has a greater impact on the veracity of the rumor prediction.

4. Improved Understanding of Nuance: Fake news often involves complex combinations of text, images, and other elements. Multi-modal learning can capture these complex relationships and subtle nuances that are essential for accurate detection

IV. IMPLEMENTATION

Modules:

1.Data Collection and Preprocessing Module.

- Collects social media posts containing both textual and visual (image/video) content.
- Performspreprocessingtasks:
  - Text cleaning (removal of noise, symbols, etc.)
  - Image resizing and normalization
  - Handling missing modality cases (e.g., posts with only text or only image)

2. FeatureExtractionModule

- Extracts features from multiple modalities:
- **Textual Features:** Using BERT,Long Short Term Menory, or other language models.
  - **Visual Features:** Using CNNs or pre-trained models like ResNet or Vision Transformers.
  - **Social Context Features:** Includes user profiles, propagation patterns, or interaction graphs.

3. Multi-ModalFusion Module.

- Combines features from text, image, and other modalities.
- Fusiontechniquesmayinclude:
  - Earlyfusion(concatenationat feature level)
  - Late fusion (combining outputs of separate models)
  - Attention-based or fine-grained fusion for deeper interaction.

4. Meta-Learning Module

- Implements meta-learning strategies to enablequickadaptationtonew,
- unseen rumor events.
- Supports few-shot learning for detectingrumorswithlimitedlabeled data.
- Learns task-agnostic knowledge that generalizes across different rumor patterns.

5. Multi-TaskLearning Module

- Simultaneously trains on related tasks to improve overall model performance:
  - **Rumor Detection:** Classifying whether a post is a rumor or not.

- **StanceDetection:**Identifying public stance (support, deny, query, etc.).

METHODOLOGY

1. DataCollection

- Collect social media posts from platforms such as Twitter, Weibo, or Reddit.
- **Gatherposts containing:**
  - Textualcontent(tweets, captions,descriptions)
  - Visualcontent(images,videos)
  - Socialcontext(user information,interaction patterns)
  - Label the data for rumor detection and related tasks (e.g., stance detection, source credibility).

2. DataPreprocessing

- Clean and tokenize text data.
- Removing noise and irrelevant symbols.
- Handleincompletemodalitycasesby designing the system to deal with missing images or text.
- Generate auxiliary labels for multi-task learning.
- Examples of Data Preprocessing-Stance Labels.

3. FeatureExtraction

- Extract meaningful features from each modality:
  - **Text Features:**Using models like BERT, Roberta, or LSTM networks.
  - **Image Features:** Using CNNs, Vision Transformers, or pre-trained models (e.g., ResNet).
  - **Social Context Features:** Graph-based features from user interactions or propagation patterns.

4. Multi-modalFusion

- Combine the features from different modalities using advanced fusion techniques Like-
- **EarlyFusion:**
  Concatenate feature vectors.
- **LateFusion:**
  Combineoutputs from separate models.
- **Fine-grainedFusion:**
  Utilize attentionmechanismstoalign andintegratefeaturesat different levels.
- **Hybrid Fusion:**
  A flexible approach that combines elements of both early and late fusion, for example, fusing some modalities early and others late.

5. Meta-LearningFramework Implementation

- Integratemeta-learningtechniquesto improve the model's adaptability to unseen rumor events.
- Apply few-shot learning or model-agnostic meta-learning (MAML) to quickly generalize to new types of rumors with minimal labeled data.

V. RESULTSANDDISCUSSION

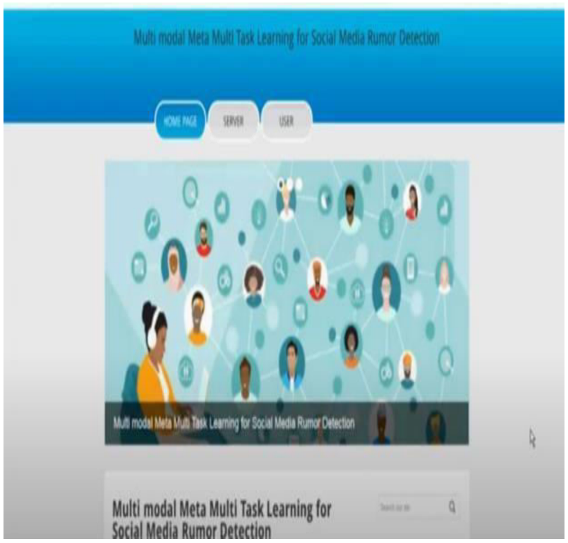

Fig1 Home Page

This interface is designed for a system focused on detecting social media rumors using multi-modal and multi-task learning techniques. It features a navigation menu withoptionssuchas"HomePage,""Server," and"User"foreasyaccess.Thecentral imagehighlightstheinterconnectednessof users, representing data flow and interaction acrossplatforms.

Thetitleclearlyindicates the system's aim: "Multi-modal Meta Multi-

TaskLearningforSocialMediaRumor Detection."

Fig2 LoginPage

The interface showcases a system designed for detecting rumors on social media using advanced multi-modal and multi-task learning methods. It features a clean layout with navigation options like Home Page, Server,andUserforsmoothuserinteraction. A central illustration visually represents a network of diverse users connected through shared information. The system aims to enhance the reliability of online content by identifying and managing misinformation effectively.

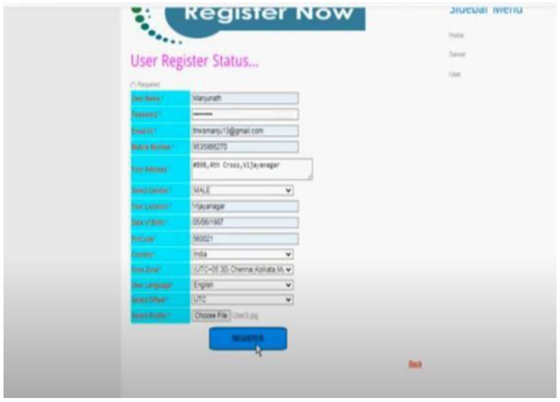

Fig3UserRegistrationPage

This system is designed for social media rumor detection using multi-modal meta multi-task learning. The interface includes navigation options like Home Page, Server, and User for easy access. An illustration in the center shows connected users, symbolizing information sharing across networks. The goal is to detect and prevent the spread of false information on social media platforms.

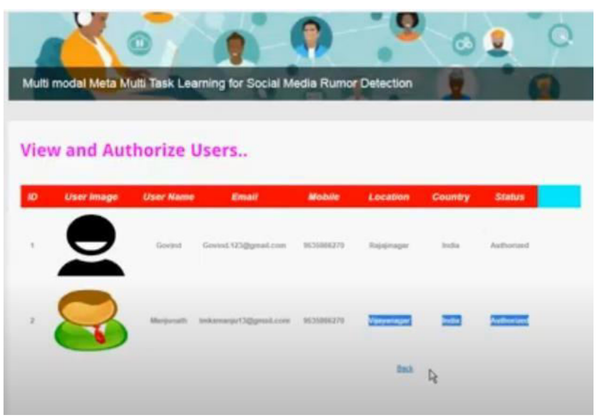

Fig4UserAuthorization Page

Theplatformfocusesondetectingrumorson social media using multi-modal meta multi-task learning techniques. It features a user-friendlyinterfacewithnavigationbuttons like Home Page, Server, and User. The central image represents a network ofdiverseindividualssharinginformation.This system aims to identify and control the spread of misinformation effectively.

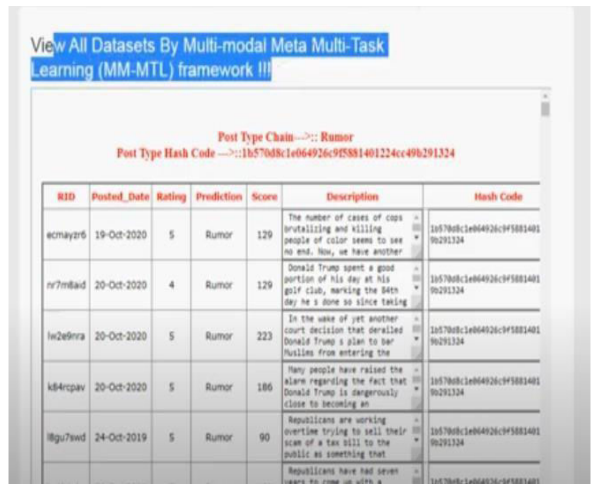

Fig5 DatasetPage

The image displays a table presenting datasets within a "Multi-modal Meta Multi-TaskLearning(MM-MTL)framework." Thisframeworkseems to categorize and analyze various online posts or news snippets, potentially identifying them as "Rumor" based on a prediction model. The table includes details such as posted dates, ratings, predictions, descriptions of the content, and associated hash codes. The descriptions in the table contain text relating to current events or public figures, suggesting a focus on social media analysis or misinformation detection.

Fig6Resultsin Graph

The image shows a bar graph, which is a common visualization used to represent qualitative data.

Purpose: Bar graphs depict qualitative data that has been summarized in a frequency distribution.

Structure: Labels for categories are typically on the horizontal axis, and bars above each label represent the frequency or count for that category.

Application: Histograms, a related type of graph, are used for grouped frequency distributions with continuous classes, showing the distribution of data.

VI.CONCLUSION

This researchpresents a unique Multi-modal Meta Multi-Task Learning (MM-MTL) framework for the detection of social media rumors.Wespecificallyintendtoenhanceth e efficacy of rumor detection by utilizing the stance information derived from users' comments in stance detection. Unlike conventional multi-task learning approaches that utilize shared lower layers for common feature extraction, MM-MTL employs shared higher meta network layers, which encapsulate the meta-knowledge inherent in multi-modal posting. The collective meta- knowledge subsequently enhances each task by dynamically producing the parameters of the task-specific models. Additionally, we utilize the attention mechanismto assess the significance of each response, hence enhancing the extraction of semantic information embedded within the nuanced stance labels. Comprehensive studiesontwo Twitter benchmark datasets indicate thatour suggested technique attains state-of-the-art performance. In the future, we will incorporate other rumor-related tasks intothe multi-modal meta multi-task learning architecture, including the evaluationofuser trustworthiness.

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AUTHOR DETAILS

Mrs.J.KUMARIisan Assistant Professor in the Department of MCA at QIS College of Engineering andTechnology,Ongole, Andhra Pradesh. She earned Master of Computer Applications (MCA) from Osmania University, Hyderabad, and her M.Tech in Computer Science and Engineering (CSE) From Jawaharlal Nehru TechnologicalUniversity,Kakinada(JNTUK). Her research interests include Machine Learning, programming language. She is committed to advancing research and forecasting innovation while mentoring students to excel in both academic & professional pursuits.

Mr.Y.SUDARSHAN BABU is a postgraduate student pursuing aMCAin the Departmentof ComputerApplications at QIS College OfEngineering& Technology, Ongole an Autonomous college in Prakasam dist. He completed his undergraduate degree inB.Sc(Physics) from (AcharyaNagarjuna University).

His academic interests include Cloud Computing and Artificial Intelligence.