Model	Accuracy	F1-score
Proposed SP-MT (Fig. 2)	**93.95**	**90.24**
LR (Argyris et al. 2021)	81.48	81.00
ESD (?)	89.65	85.11
HAN (?)	89.47	86.00
AT-JSS-LEX (?)	88.02	84.01
MNB (?)	85.44	78.08
DNN (?)	84.61	76.23
SVM-ngram (?)	85.55	66.33

Table 9: Results of Proposed Framework SP-MT with baselines on our Climate Change Dataset

Model	Atheism F_{avg}	Climate F_{avg}	Feminism F_{avg}	Hillary F_{avg}	Abortion F_{avg}	Mac F_{avg}
Proposed SP-MT(Fig.2)	69.5	**63.5**	**63.2**	67.5	**70.5**	**66.84**
ESD (Vychegzhanin and Kotelnikov 2021)	66.64	43.82	62.85	67.79	64.94	61.20
HAN (?)	**70.53**	49.56	57.50	61.23	66.16	61.00
AT-JSS-LEX (?)	69.22	59.18	61.49	**68.33**	68.41	65.33
SVM-ngram (Sobhani, Mohammad, and Kiritchenko2016)	65.19	42.35	57.46	58.63	66.42	58.01

Table 10: Results of Proposed Framework SP-MT with baselines on SemEval 2016 Dataset

quency of unigrams and bigrams extracted using TF-IDF and find that some of the denier's tweets containing either rarely used keywords or keywords frequently used in believers' tweets were misclassified. For example, the denier's tweet in example 7 (table 7) contains words such as *real, snow overnight*, which are most commonly found in believers' tweets and confuse the model and lead to an incorrect prediction. **(iii)** We investigated that of the total misclassified denier tweets, 35.7% of the tweets contained sarcasm to express their denial. Of the sarcastic denier tweets, 50.16% of the tweets have positive sentiment, 31.70% have neutral sentiment, and the rest have negative sentiment, while 25.78% of the misclassified believer tweets have sarcastic labels (examples 8 and 9 of table 7). The labeling of sarcasm is based on the majority vote of three trained annotators with an interrater agreement of 0.78, calculated with the Fleiss-Kappa measure. This motivated us to investigate the presence of sarcasm in climate change tweets to further improve the performance of the model as a part of our future work.

7 Privacy and Ethics

Although social media offers innovative ways to raise awareness about climate change, phenomena such as climate denial and climate delay have become a serious problem for scientists and the government to convince people of the importance of understanding the current climate crisis. Climate change deniers are not only skeptical about climate change but also emphasize the disadvantages of all measures proposed to combat climate change and abandon the idea that it is not possible to prevent climate change. This often leads to the spread of misinformation, resulting in a delay in the implementation of effective climate change mitigation measures (**?**). Since our work is dedicated to classifying Twitter content into climate change deniers or believers, the proposed approach can be useful for government agencies, researchers, and tech companies that monitor such content on social media to identify and intervene tweets from climate change deniers. The proposed approach is useful in combating climate misinformation by identifying posts by climate change deniers and reducing the spread of such content that is deemed false or misleading.
The input feature of the proposed model, such as the tweet text, is available as soon as the user posts something. However, the topic feature can be extracted by performing topic modeling for a collection of tweets after a fixed interval, e.g., after every 5, 10, 15, or t minutes of duration. Therefore, our proposed approach can be used in a real-time environment by interested agencies and authorities to classify social media content into one of the two polarized classes.
Although we conduct our work with public data from social media, however, we are committed to protecting the privacy of individuals and therefore avoid providing personally identifiable content. The dataset that is made publicly available consists only of tweet IDs and comments.

8 Conclusion and Future Work

In this paper, we focus on the importance of classifying Twitter content into climate change deniers and believers, because climate change deniers emphasize the downsides of any action to address climate change, which often leads to the spread of misinformation and delays the implementation of effective action to mitigate climate change. Our proposed approach, implemented in real-time, can be useful for government agencies, researchers, and tech companies in combating climate misinformation by identifying content that denies climate change and reducing the spread of such posts that are considered misleading.
In this work, we investigated the role of sentiment in classifying stance of the tweets related to climate change. We curate a novel dataset that includes annotations for both stance detection and sentiment analysis tasks, which will be useful to the research community in exploring other needed classification tasks. We propose a shared-private multi-task framework for the optimization of stance detection task benefiting from the sentiment analysis (auxiliary task). The proposed module uses feature-specific and shared-specific attention to fuse multiple features and learn useful and relevant private and shared features for both tasks. The results show that multi-tasking increased the performance of the stance detection task compared to its uni-modal and single-task variants. Although we examined the performance of the proposed approach in detecting attitudes in the domain of climate change, the performance of the model on the SemEval dataset shows that it is much more broadly applicable beyond the domain of climate change, suggesting that our framework can generalize well in different domains. Future work will attempt to analyse what other aspects of natural language, such as sarcasm, aspect-based sentiment, and emotion recognition, might help to more accurately classify attitudes toward climate change. The inclusion of other modality encodings such as images, emoji, and advanced architectures will also be the subject of our future work.

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