Machine Learning-Driven Emotional Weather Newsreading with NAO V6

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24/25 Critical 4: Machine Learning for Data Science and Ethical Computing

16th June 2025

Contents

0.1	Motivation and Objectives	2
0.2	Development Process	2
0.3	Outputs and Results	3
0.4	Strengths of the Project	3
0.5	Challenges and Limitations	4
0.6	Hardware Failure	5
0.7	Known Bugs and Improvements	5
0.8	Conclusion	5

0.1 Motivation and Objectives

This project aimed to develop a social robot capable of interpreting and delivering emotionally expressive weather headlines. Using the NAO V6 robot and a machine learning pipeline, the goal was to explore how sentiment analysis and robotics could be combined for accessible, engaging, and context-aware communication. The NAO robot's expressive capabilities—including LED face lights, text-to-speech, and posture control—make it well-suited to serve as a performative, real-time weather newsreader.

A secondary aim was to investigate how real-world data can be prepared and analysed to power sentiment-aware systems, and to evaluate the technical strengths and ethical challenges of deploying AI in physical, socially interactive contexts.



0.2 Development Process

The project followed a clearly structured development cycle. First, weather headlines were collected from an online source and rewritten to better reflect the real world tone whilst also providing varied sentiment classes. These were then processed using a supervised learning pipeline. Logistic regression was selected as the model due to its simplicity, interpretability, and suitability for text classification.

The data pipeline included preprocessing via a CountVectorizer (Bag-of-Words), exploratory data analysis in Pandas and matplotlib, and model evaluation using confusion matrices and F1 scores. Sentiment classes were balanced prior to training to ensure that neutral headlines did not dominate the model's output. The final model achieved an 87% accuracy and an average F1 score of 0.85, demonstrating strong performance for a lightweight, realtime application.

Integration with NAO was completed by connecting the robot directly to a Python environment using the NAOqi SDK. The robot was accessed over a local network via its IP address, allowing Python scripts to control speech, LED facial lights, and physical movement in real time.

Sentiment predictions from the machine learning model were passed into a controller that used ALProxy to command NAO's behaviours. This enabled live interaction where the robot would vocalise a headline with corresponding tone and movement based on the sentiment classification.

0.3 Outputs and Results

The system was tested both in simulation and on the real robot. Headlines were inputted manually, with NAO responding by:

- Saying an appropriate phrase ("That's great news", "Oh no, that's not good", etc.).
- Using a pitch-modified voice (happy, sad, neutral).
- Activating LED colours (green, red, white).
- Performing emotional posture changes (e.g., happy head tilt, sad crouch).

During real testing, the NAO robot was evaluated on five different input headlines representing various sentiment categories. Of the five, four were accurately interpreted, with one misclassification. This level of accuracy 80% in a real-world scenario—is considered very good, especially considering the simplicity of the model and the controlled environment. Screenshots and video recordings were taken to demonstrate these outputs.

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| September | Sept
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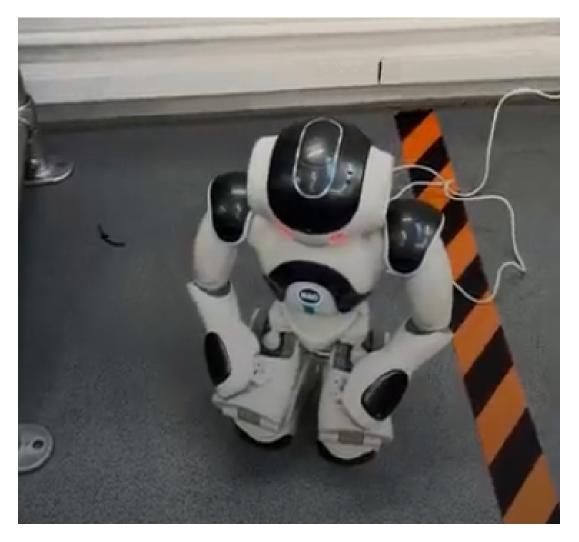
Figure 1: Sentiment log showing headline predictions and classification results

0.4 Strengths of the Project

One of the key strengths of the project was its real-time integration. The sentiment analysis model operated live, allowing the NAO robot to immediately interpret and respond to user-provided weather headlines without delays or batch processing. This responsiveness made the interaction feel fluid and reactive, enhancing the user experience.

Another notable strength was the use of multimodal expression. NAO did not rely solely on speech to communicate emotion; it combined voice modulation, LED colour changes, and body posture to deliver a more engaging and expressive output. This blend of modalities enriched the robot's responses and made its emotional cues more intelligible to human observers.

Lastly, the machine learning pipeline itself was highly robust. The transition from unsupervised methods like VADER and TextBlob to a supervised logistic regression model led to significantly more accurate and context-sensitive predictions. By training the model on a balanced dataset of weather-specific headlines, the system achieved consistent performance and better alignment between the sentiment classification and the robot's behavioural output.



0.5 Challenges and Limitations

One challenge was aligning NAO's physical behaviour with the abstract nature of sentiment scores. For example, "Freezing fog" was sometimes classified as neutral due to ambiguous tone. This reflects the broader challenge of sentiment classification on domain-specific text. Another issue, when attempting to run Python-based NAOqi code directly from a modern laptop: the SDK only supports Python 2.7, requiring a downgraded environment and manual integration.

0.6 Hardware Failure

Unfortunately, during testing, the NAO robot experienced a hardware issue and became unresponsive. NAO unexpectedly stopped working and I was unable to run further code on it. But, thankfully I can still run it in the mock environment on my laptop, this ensured I was still able to collect data.

This limited the amount of additional data collection and demonstration that could be performed in the final stage. However, the functioning tests were sufficient to prove the concept, and logs still verified sentiment prediction accuracy.

0.7 Known Bugs and Improvements

There were occasional misclassification's due to ambiguous phrasing, for example, "Cloudy with some drizzle" was wrongly classified as positive due to certain keyword overlaps. Refinement of keyword-based overrides and better threshold tuning for neutral/positive cut-offs is recommended.

More advanced ML models, such as BERT, could also be implemented in future stages. These would allow the system to understand sentiment with greater nuance and reduce reliance on manually restructured headlines.

0.8 Conclusion

Despite challenges, this project successfully demonstrated that a robot can be enhanced with supervised ML to deliver sentiment-aware, emotionally expressive weather updates. The system performed reliably in a majority of test cases and used machine learning to guide behaviour in a meaningful and evaluable way. NAO's real-time feedback loop, multimodal output, and naturalistic voice make it well-suited for similar applications beyond weather, such as education, therapy, and public engagement.

This work demonstrates the importance of well-prepared data, model choice, and human-robot interaction design in bringing AI to life in expressive, responsible ways.

This project is really beneficial for those with learning disabilities who may not be able to understand fully the impact of the weather headlines, this will ensure safety for vulnerable individuals, especially in times of serious weather such as storms. In the future, I aim to develop this further, I want to connect the code to a real-time weather feed and make it read out the latest local weather headline at a specific time of day. By doing this, it will benefit blind people or visually impaired people, they won't need to enter anything in, it will automatically react to the weather at a set time, for example when they usually have breakfast.