# Using Multimodal Data and AI to Dynamically Map Flood Risk

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Big Data Analytics

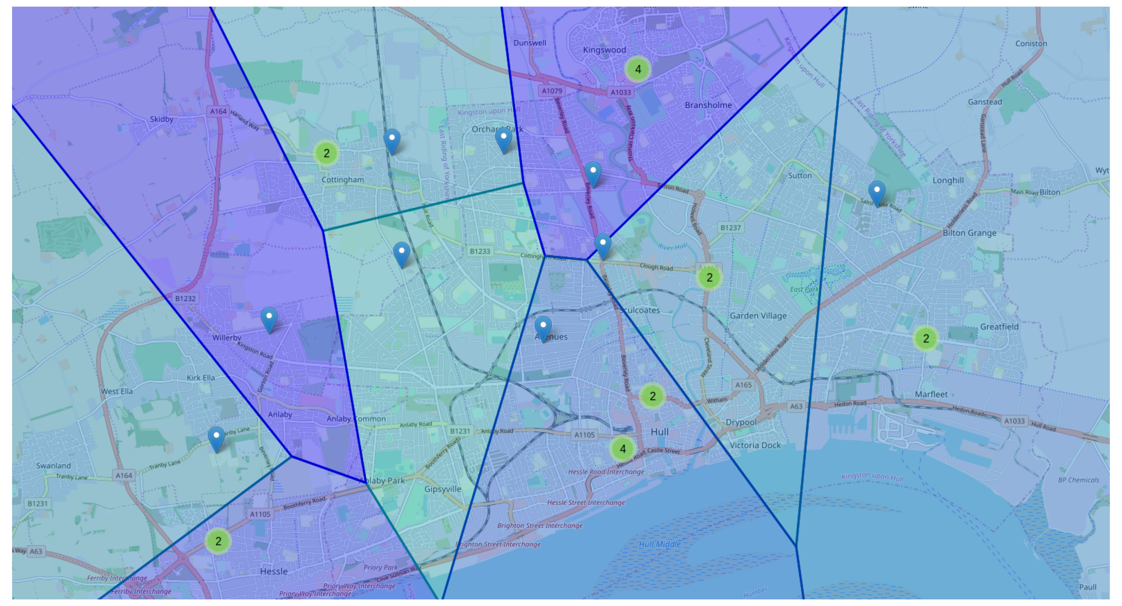
## Motivation

Traditional flood modelling systems rely on readings from sparsely located static weather stations and computationally expensive physics-based simulations that **can't react in real-time**. Existing solutions for predicting floods or flood risk:

1. Use a single data source (e.g. river levels, drainage networks, etc)
2. Social media: use simple keyword analysis
3. Rely on physics-based simulations that can take a long time to run

With this in mind, we want to:

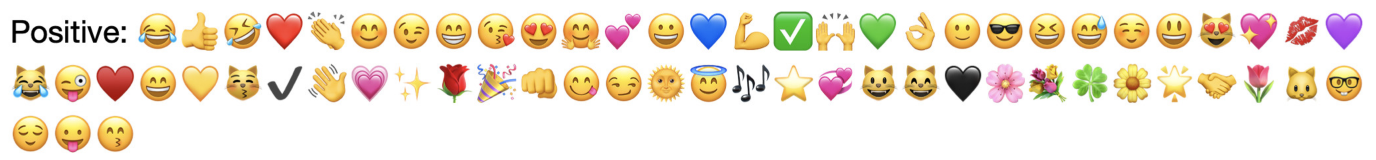
1. Explore contemporary artificial intelligence (AI) models for predicting flood risk in multiple dimensions at once.
2. Use a range of heterogeneous data sources - everything from rainfall radar data to social media posts.
3. Enhance situational awareness with real-time predictions.



Ultimately, we want to build a system that is capable of predicting flood risk in real-time.

## Social Media

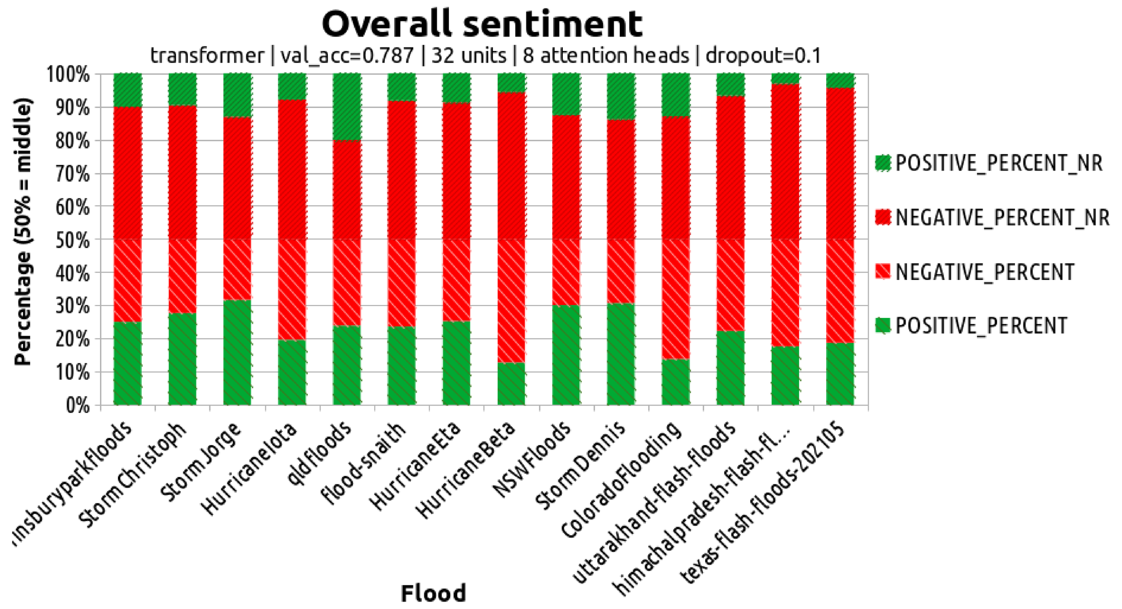
By analysing tweets from twitter, we hope to identify humanitarian needs and the worst affected areas during a flooding event. Example hashtags we have downloaded data from include `floods`, `flashfloods`, `StormChristoph`, `NSWFloods`, and more.





To do this, we are classifying social media posts into positive / negative sentiment categories by the emojis used using a transformer encoder AI model, and have currently achieved a validation accuracy of **79.6%**.

In an initial analysis, we found that overall, replies to tweets are more positive than the original tweets themselves (see below).

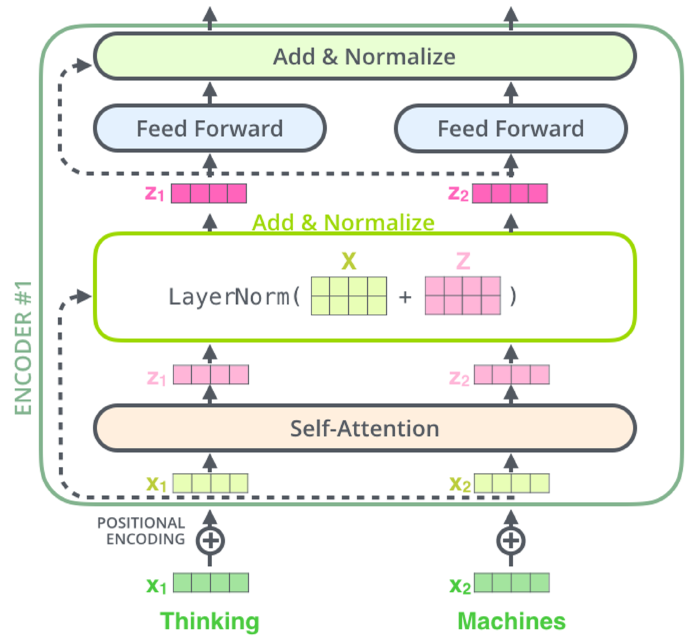


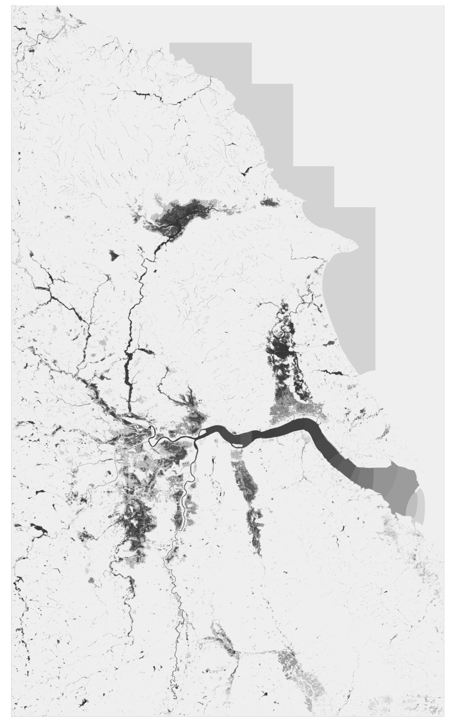

We also tried classifying images associated with tweets by the predicted sentiment of the tweet using a ResNet50, and achieved an accuracy of **60.6%**.

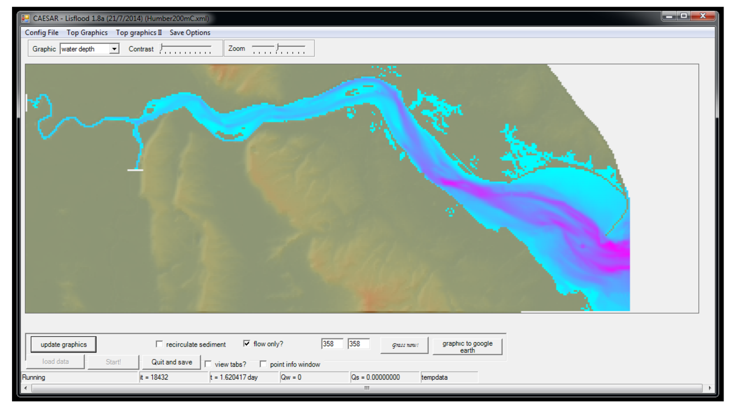
## Data Fusion

A focus of this project is combining multiple heterogeneous data sources. We will achieve this in 2 phases.

In the first part, we will use CLIP [2] to combine both tweet text and social media image together to predict positive / negative sentiment with the goal of increasing overall accuracy.





In the second part, we will look at combining the rainfall radar AI model with the social media models. We plan to investigate multiple options, such as using a rainfall radar model to direct the attention of a social media model, or vice versa. In doing so, we could for example catch and analyse tweets that may otherwise have been missed.

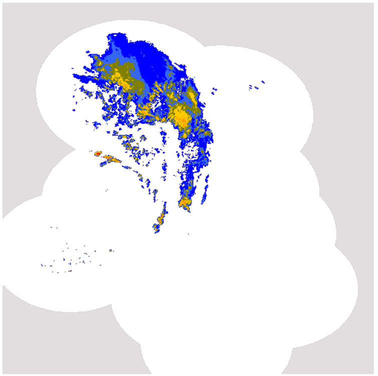
By combining multiple different data sources, we plan to increase accuracy and overall situational awareness by processing a range of information in real-time.

## Rainfall Radar

Inspired by [1], we are exploring predicting water depth from rainfall radar data and a heightmap.

**2 dimensions:** By running a physics-based model (CAESAR-Lisflood), water depth information can be obtained as labels (see left) for an AI model.

**Classification:** With an autoencoder-based architecture, we intend to train a classifier that predicts whether cells in a 2d map contain water or not.



Future plans include predicting classes of water depth and testing the model's generalisability.

## Future Work

In the future, we aim to:

1. **Social media:** We will use CLIP to combine text and images to improve sentiment prediction accuracy. We will also investigate using topic and/or geographic analysis to identify the primary topics being discussed, and how people feel about them.
2. **Rainfall radar:** Work on implementing the rainfall radar-based water depth prediction model. Once implemented, we will measure the model's performance and generalisability.
3. **Data fusion:** We will explore combing the above 2 approaches by using 1 to direct the attention of the other. In this way, we hope to increase prediction accuracy and performance.

## References

[1] Charlotte Pelletier et. al. Temporal Convolutional Neural Network for the classification of satellite image time series . *2019 Remote Sensing*.

[2] Alec Radford et. al. Learning Transferable Visual Models From Natural Language Supervision . In *ICML 2021: 38th International Conference on Machine Learning*.

[3] Ashish Vaswani et. al. Attention is All you Need . In *Proceedings of the 31st International Conference on Neural Information Processing Systems*.