CA4021 Final Year Project Proposal - Fog Nowcasting at Dublin Airport

Joseph Oluwasanya
joseph.oluwasanya2@mail.dcu.ie
Student ID: 19329261

Julita Swiatek
julita.swiatek2@mail.dcu.ie
Student ID: 19766375

Supervisor: Tomas Ward

December 22, 2022

Executive Summary

In this project, we aim to improve the fog nowcasting capabilities at Dublin Airport, Ireland using machine learning and analysis-derived insights. We will carry out exploratory data analysis on 10 years of hourly-collected weather data provided by Met Éireann. Then, we will develop a machine learning model to predict, at 1 hour lead time, the presence of fog at Dublin Airport. This will aid Air Traffic Controllers in planning aircraft operations and safely managing aircraft flow. Numerical Weather Prediction (NWP) models are large physics-based models used for mesoscale weather forecasting by meteorologists. In Ireland, the Harmonie-Arome model is used for weather forecasts. These models are effective at forecasting weather conditions, as we see with daily weather forecasts, but short-range forecasting at small domains; small being, say, less than 2×2 km in ground surface area, using numerical weather models is a very complex process. NWP models have been shown to underperform in the fog nowcasting task in comparison to their precipitation forecasting skill in recent research (Zhou et al. 2012, Román-Cascón et al. 2012). Here we will use a more data-driven approach than the deterministic model-driven approach of NWP. We will build a machine learning model with the aim to outperform the Harmonie-Arome model at fog nowcasting (short lead-time fog prediction) at Dublin airport, using its performance as a benchmark. As part of the evaluation, we will test the model's forecasting skill for the onset and dissipation of fog. We will also carry out an analysis of weather observations coming from the weather station at Dublin airport for the years 2011 to 2021.

1 Motivation & Background

When visibility at an airfield falls below certain levels, airports are forced to implement low-visibility procedures. The guidelines vary for each airport, but they must operate at reduced capacity under these procedures. These measures are put in place because most often, in low visibility conditions, the autopilot is engaged for landing, and operates solely based on signals from the Instrument Landing System (ILS). The ILS signal can be distorted by other planes in the vicinity. Each aircraft that lands or takes off, therefore, needs to have more separation from the previous one than under normal operating conditions. This in practice can mean double the normal separation distance, which greatly reduces airport capacity and causes delays. Air Traffic Controllers' actions during fog events can include reducing taxiway occupation, prolonging periods between takeoffs and landings, and even suspending airport operations to avoid runway incursions and other possible incidents. Air Traffic Controllers also consider the fact that missed approaches are a lot more common during fog events due to insufficient visibility of the runway.

It is therefore crucial that airports have the most up-to-date information on weather conditions so that Air Traffic Controllers can safely carry out their work, decide the airport capacity and plan aircraft operations accordingly. The rapid onset of fog causes delays and, consequently, financial losses for airports (Huang & Zhang 2017, Wu et al. 2012). Moreover, conducting operations in reduced visibility can create dangerous situations. Large-scale NWP models have been shown to underperform on hyper-localised fog prediction tasks (Zhou et al. 2012, Román-Cascón et al. 2012). Met Eireann use the Harmonie-Arome NWP model for their forecasts, which has been evaluated in many fog prediction studies (Román-Cascón et al. 2019, Steeneveld et al. 2015). We will build a machine learning model for fog nowcasting at Dublin Airport, aiming to outperform the model currently in use.

A highly accurate model for predicting fog would help Air Traffic Controllers to determine the current airport capacity, manage the aircraft flow and, ultimately, improve safety at the airport. If the model is successful, there is a possibility of it being scaled and implemented in other parts of the country (or the world), in the long run improving timeliness of flights. Additionally, any discovery made while undertaking this project will undoubtedly help to better understand the best methods of predicting fog, as well as the correlation between fog and other weather events.

2 Problem Statement

As discussed in Section 1, Meso-Scale NWP systems, such as the Harmonie-Arome system used for weather forecasts in Ireland, struggle with hyper-localised fog forecasts. The goal of our project is to produce an accurate fog nowcasting model such that we can predict whether there will be fog in the next hour, at Dublin Airport, County Dublin, Ireland. We will build machine learning models using observational weather data, collected by Met Éireann at the Dublin Airport weather station. Note that fog is a rare weather event, so the available data is highly unbalanced. Using observational weather data, machine learning fog prediction models trained on data from a single region usually do not transfer effectively across different countries and regions. For this reason, our solution is designed for use at Dublin Airport specifically. The definition of fog according to the World Meteorological Organization (WMO) is horizontal visibility of less than 1000m on the ground (WMO n.d.). There are many different types of fog, defined according to how they are formed. Below is a brief description of the types that occur most often in Dublin.

Radiation fog forms on a cloudless night, when the land surface loses heat to the atmosphere by radiation. Moist air in contact with the cooling surface also cools and when the temperature falls below the dew point for that air, given there is a light wind, fog forms. As the sun rises, the surface temperature increases and the fog will eventually disperse. This kind of fog is common in the autumn months in northern Europe. Advection fog happens when a warm, moist air mass flows across a colder surface. Fog will form when the air mass is cooled from below by the colder surface, given the temperature of the air mass is reduced to the dew point. The dew point is the temperature the air needs to be cooled to in order to achieve a relative humidity (RH) of 100% (US Department of Commerce n.d.). Advection fog can be accompanied by winds of any force (not just light wind). This kind of fog occurs regularly in springtime in the coastal areas of northwestern Europe. We will also analyse the weather data to gain a better understanding of weather trends relating to low-visibility events at the Airport. More details on this in Section 4.

3 Literature Review

3.1 Fog studies

Fog event prediction is not a new field of investigation, but has recently become a more intensive research area. Early studies produced fog climatologies for specific, isolated events (Bendix 2002, Belo-Pereira & Santos 2016). Fog persistence has been studied by analysing the effects of physical and chemical features on the persistence of fog (Stolaki et al. 2015). Stolaki et al. (2015) investigate the sensitivity of fog to aerosols through the impact of cloud condensation nuclei on fog droplets, studying a specific radiation fog event recorded at the SIRTA Observatory near Paris in 2011. They did this using the Meso-NH (Lafore et al. 1998) atmospheric simulation system. Aerosols act as the substrate on which fog droplets form, so a better understanding of their impact on the fog life cycle is useful for predicting fog properties such as persistence. More recently, fog persistence has been studied from a statistical viewpoint (Cornejo-Bueno et al. 2021, Salcedo-Sanz et al. 2021). Cornejo-Bueno et al. (2021) found that heavy-tailed probability distributions gave the best fit for fog event durations at the A-8 motor road, Falicia, Spain, irrespective of the season. These were namely, the Log-Normal, Generalized Extreme value, and Generalized Pareto distributions. As part of our study, we will investigate the persistence of fog events at Dublin Airport, Ireland. We noted however that the temporal resolution of data used in their study was 5 minutes, while we have a less fine resolution of 1 hour.

3.2 Numerical Weather Prediction

Much work in fog nowcasting focuses on the use of Numerical Weather Prediction. NWP uses mathematical models of the atmosphere and oceans to produce weather forecasts based on current weather conditions. A series of nonlinear differential equations are used to model atmospheric processes like radiation and convection. These are solved by NWP models using numerical methods to predict the evolution of the atmosphere, yielding weather forecasts. From this, predictions of precipitation, air pressure, temperature, cloud cover, and wind speeds are attained. To produce forecasts, NWP models require the initial conditions to be set such as weather observations (coming from weather stations and satellites) and information at the boundaries of their domain. Their output is deterministic, a single forecast dependent on the set of initial conditions.

Works studying the use of NWP models for fog prediction usually deal with mesoscale numerical models, which give forecasts in the kilometre resolution (Bergot et al. 2007). Bergot et al. performed a comparative analysis of fog simulations from 6 different numerical weather models at Paris-Charles de Gaulle airport. The goal of the study was to identify how capable different numerical weather models were of forecasting fog. It was recognized that fog prediction using NWP is still a difficult problem and that predictions are highly sensitive to parameterizations of both atmospheric and ground processes (Román-Cascón et al. 2012). NWP models are often used in ensemble-based forecasting systems as a result of this. For example, the use of 10 Harmonie-Arome runs in the Irish

Regional Ensemble Prediction System (*Launch of Ireland's high resolution ensemble-based forecasting system - Met Éireann - The Irish Meteorological Service* n.d.), and the state-of-the-art HREF system used by the NOAA in the United States for weather forecasts (Roberts et al. 2019).

Zhou et al. (2012) looks at the performance of the WRF-NMM model for predicting fog in North America. This work showed that Numerical Weather models underperform at fog prediction in comparison to precipitation forecasts from the same models. Román-Cascón et al. (2012) also studied the use of the WRF model for predicting fog, but at the Spanish Northern Plateau, located near Valladolid Airport, Spain. They used different parameterisations of the physical properties of the earth's surface and atmosphere, performing statistical analysis of the results. It was found that for a single physical parameterization, the results varied depending on the period being studied due to differences in the features of each fog episode. This made it difficult to generalize the results. In 2019, it was shown that both the WRF and Harmonie-Arome NWP systems, with the same configurations, are better at forecasting cloud-base lowering fog than radiation fog (Román-Cascón et al. 2019). Although the models tended to over-predict the vertical height of CBL fog. The inability to effectively model fog formation and dissipation is highlighted as a weak point in Numerical Weather Prediction (Steeneveld et al. 2015, Román-Cascón et al. 2016). More recently, in 2019 the Harmonie-Arome model has been shown to perform well at predicting low-visibility events at Norte Airport, Tenerife, with a False alarm rate of approximately 35% (Fernández-González et al. 2019). Note though that Fernández-González et al., as well as previous works, have shown that NWP fog nowcasting is extremely sensitive to small fluctuations in environmental variables which we still struggle to parameterize in numerical weather models.

Met Éireann use the Harmonie-Arome model for weather forecasting, including fog prediction. Harmonie-Arome is a mesoscale NWP model used for short-range weather forecasts. It is operational in many European countries including Ireland, Denmark, Estonia, and Lithuania (Bengtsson et al. 2017). In Ireland, Met Éireann runs Harmonie-Arome in the following domain. 1000 x 900 grid points at 2.5-kilometre resolution, with 65 levels of vertical (*NWP in Met Éireann* 2011). Localised fog predictions from the Harmonie model in the Dublin airport region will serve as a benchmark for our predictive model.

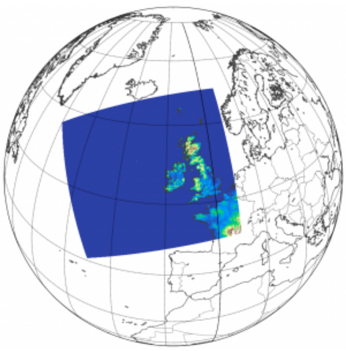

Figure 1: Met Èireann domain for Harmonie-Arome forecasts.

3.3 Fog prediction with Machine Learning

Fog prediction as a machine learning task is framed as the prediction of horizontal visibility. As a regression task, models are trained with visibility as the target variable and use weather observations as predictors. The objective in this case is to predict future visibility values. As a classification task, fog prediction using ML involves setting the visibility threshold at 1,000 metres such that any visibility observation below this is considered fog. The horizontal visibility threshold is conventionally 1,000 metres, in line with the definition of fog by the World Meteorological Organisation. Fog nowcasting using machine learning has been a recurring research topic since the 80s. One of the earliest examples of using ML techniques to predict fog was Koziara et al. (1983). They used a model output statistics (MOS) scheme using a stepwise-selection multiple linear regression approach to estimate marine fog probability at 24h intervals for the North Pacific Ocean. They found that their approach outperformed their competitors, achieving on average 78% accuracy. It is important to note that Koziara et al. reached this result using data from the summer months of 1976,1977 and 1979 only. More recently, Boneh et al. (2015) used a Bayesian decision network for fog forecasting at Melbourne Airport. They had 34 years' worth of data and found significant improvements in accuracy over the previously used operational forecasts. They achieved AUC scores of 0.9, and their network was accepted by the Australian Bureau of Meteorology and has been in use since 2006.

Kim et al. (2022) approached fog nowcasting as a regression problem, predicting visibility levels using ML approaches such as Artificial Neural Networks (ANN), Extreme Learning Machines (ELM), k-Nearest Neighbours, Support Vector Regression (SVR) and Extreme Gradient Boosting (XGB) to predict visibility in Seoul, South Korea. They had 3 years of observational weather as well as particulate matter data for training and testing their models. Kim et al. found that XGB performed the best out of all the algorithms, even outperforming ANN, achieving RMSE of 0.08km for the training data and 2.08km for the test data. However, they used a random sampling method without replacement for creating their training validation and testing datasets. This can lead to an overestimation of performance due to the loss of time-series context (Vorndran et al. 2022). Cornejo-Bueno et al. (2021) used 2 years of data when they explored low-visibility events in Spain. They chose a neural network approach, trained by the ELM algorithm, and achieved a high accuracy within a half-hour time horizon, with a Pearson correlation coefficient of 0.8. Most modern ML approaches to predicting low-visibility events, which include fog formation and dissipation, focus on the use of Neural Networks. Below are examples of papers which report good results in using Neural Networks for fog prediction.

Fabbian et al. (2007) chose to use ANNs under the assumption they would be better suited to problems involving complex nonlinear interactions. They had 44 years of meteorological observations obtained from the Australian Bureau of Meteorology. Forecasting aids for 3-, 6-, 12-, and 18-h lead times were developed and they found that their model performed well for all four lead times, as well as being robust to error perturbations for various error parameters. Fabbian et al. measure model performance as the area under ROC curves, with results of 0.94,0.86,0.85 and 0.84 respectively for all lead times. Miao et al. (2020) developed a Long-Term Short Memory (LSTM) network, claiming it could learn long-term dependence information and avoid gradient explosion and gradient disappearance problems during the training period. Among other evaluation criteria, they also use Threat Score (TS-Score), which is used by the Chinese national weather service to indicate the value of weather forecasting. They found that their approach significantly outperformed traditional machine learning algorithms such as AdaBoost, KNN and CNN, achieving TS-Scores of 0.61 for 1-h predictions and 0.55 for 2-hour forecasts, compared to 0.6 and 0.44 (Adaboost) respectively. Other notable approaches include Kamangir et al. (2021), with the prediction of fog visibility categories below 1600m, 3200m and 6400m for 6, 12, and 24-h lead times by using a 3-D Convolutional Neural Network (3-D CNN), which outperformed the High-Resolution Ensemble Forecast in use in the USA. Dutta & Chaudhuri (2015) proposed an ANN approach, utilising decision trees to identify dominant parameters influencing visibility. They found that with selected parameters being NO2, wind speed, relative humidity, CO and temperature, the ANN model performed the best when forecasting very dense visibility within a 50m horizontal distance, achieving an MAE of 0.58% and an RMSE of 1.13% for that category.

As can be seen from recent studies investigating the use of ML for fog nowcasting, there isn't yet a gold-standard modelling approach for this problem. Although this year, a full quantitative analysis of machine learning methods for fog forecasting, framed as both classification and regression problems was carried out at the Moñdonedo weather station, Galicia, Spain (Castillo-Botón et al. 2022). It was found that Gradient Boosting with Oversampling yielded the best model performance for the fog prediction as a classification task. We will reproduce this model for Dublin Airport weather observations as our machine learning model benchmark.

4 Methodology

4.1 Programming Environment

In this project, we will analyse hourly weather observations coming from Dublin Airport Weather Station between 2011 and 2021. Using this data, we will build machine learning models for fog nowcasting (1-hour prediction horizon). We use IPython/Jupyter notebooks in a Google Colab programming environment for development. In this way, we can share code in real-time, allowing for smooth collaboration and idea-sharing. Jupyter notebooks enable the running of code in "cells", for a quick turnover between coding and testing out ideas. As we will use primarily Google Colab for version control, we won't need to commit to the GitLab repo often but we will set up connections to our GitLab repository such that progress can still be updated. Jupyter notebooks support Python, and we will primarily use a Python data science stack for analytics and modelling. Packages we expect to use include NumPy and Pandas for data transformations and feature engineering, Sci-kit Learn for building and evaluating machine learning models and Seaborn and Matplotlib for data visualisations. We will also experiment with AutoML to find the best-suited algorithms for predicting low-visibility events, given the climate profile in the Dublin Airport area. The list of tools we use will likely extend as we proceed with the project, but this provides a basis for most of our work.

4.2 Data Source

As mentioned earlier, our data consists of weather observations, recorded hourly, at the Dublin Airport Weather Station for the 11-year period 2011 to 2021 inclusive. This was provided by Met Eireann and has about 100,000 rows and 70 columns. We received the table in CSV format, and it is 22MB in raw form. Our information includes the following: Wind speed, wind direction, air pressure, vapour pressure, temperature, relative humidity, cloud height, cloud amount in okta, rainfall, weather codes, and sea/ground/sky state indicators. This is not a full list of the variables, and an initial review of the data suggests that we will need to perform data cleaning. There are several "indicator" variables describing the quality of observations at different time points in the data. We will assess the quality of data with different indicator values, determining how to treat these data points. That is, whether to impute, remove or leave them as is.

4.3 Experiments & Development

The coding and development in this project will be focused on performing data analysis, running experiments, and building machine learning models. Our data analysis will look at the weather observations in different ways. We intend to include the following: An analysis of the relationship between visibility and other variables, which variables are most useful for predicting fog. Exploring alternative representations of our data (E.g., Principle Component Analysis, t-distributed Stochastic Neighbour Embedding) to identify weather-profile clusters. Inspecting the movement of climate over the years to assess data drift and to better understand weather trends and seasonality. Producing a fog climatology table similar to Belo-Pereira & Santos (2016), outlining fog occurrence statistics at

Dublin Airport. Analysing the distribution of fog persistence (low visibility event duration).

The objective of our ML model is to predict whether horizontal visibility will fall below 1,000m in the next hour. We will treat this as a classification problem (visibility $< 1,000$m: yes or no) with human-recorded visibility levels as the ground truth. We are framing this strictly as a classification problem because of inconsistencies in the target generation process. The raw target, visibility, is human recorded and for high visibility ($> 20,000$m), the measurements get less granular than at lower visibility levels. These high visibility levels occur most frequently in the data, so a regression model trained on "visibility" would be unreliable. As we saw from our literature review, researchers have achieved recent success with using Machine Learning for fog nowcasting. Artificial Neural Networks are used both as standalone forecast models (Cornejo-Bueno et al. 2021, 2020, Miao et al. 2020) and as postprocessors for Numerical Weather Prediction output (Marzban et al. 2007, Kamangir et al. 2021), and have been deployed operationally at several airports around the world. ANNs for postprocessing fog predictions from NWP are generally used for longer lead times than standalone models. This is because NWP models can take hours to produce a forecast, so are generally not used for the short lead times we will consider in this project. Neural Networks are well suited to fog nowcasting because of their ability to find complex nonlinear relationships in data; But they require a lot of data for training and because fog is a relatively rare event, it is difficult for Neural Networks to learn to model it effectively. Also, neural networks perform better at predicting fog when it is configured as a regression task, directly predicting visibility (Castillo-Botón et al. 2022). Gradient Boosted Decision trees have recently been shown to perform well at predicting fog as a classification task in comparison to other machine learning algorithms (Castillo-Botón et al. 2022). Ergo, we will build and test gradient-boosting models at the early stages of development.

Experiments will involve testing the machine learning models we build with different preprocessing and hyperparameter configurations. For instance, our dataset is unbalanced as fog is a rare event, so we will experiment with the use of different under and over-sampling methods and monitor which methods perform best for our task. We will also look at the use of lagged features to aid fog predictions. If we include lagged weather observations, can we improve our fog forecasting skill?

4.4 Desired Result & Evaluation

The desired result of this project is two-fold. Firstly, to present novel findings from the observational weather data collected at the Dublin Airport weather station through a series of visualisations, and tables where necessary. We aim to better our understanding of fog persistence, and the climatological trends related to fog at the airport through in-depth data analysis and portray its salient points. The second objective is to produce a machine learning model that predicts low-visibility events accurately at Dublin Airport and outperforms the system currently in use.

We will evaluate the machine learning model using a nested cross-validation approach. The internal cross-validation will be used for hyperparameter tuning while the external will be used for evaluating model performance on unseen data. As our data is time-series, we will employ a time-series splitting approach for internal cross-validation. This gives a more accurate simulation of reality for time series forecasting models than more commonly used cross-validation data splitting techniques such as kFold (Vorndran et al. 2022). The model is meant to predict future values, and with the temporal nature disregarded, the model is being evaluated on its imputation ability also, which can lead to an overestimation of performance.

As is further motivated in Vorndran et al. (2022), we will also evaluate specifically our models' ability to predict fog formation and dissipation. ML nowcasting algorithms tend to struggle with these, and they are points of interest in the application. Evaluation metrics we will use include F1, Precision, and Recall. We will also look at the use of the Heidke Skill Score, which is an

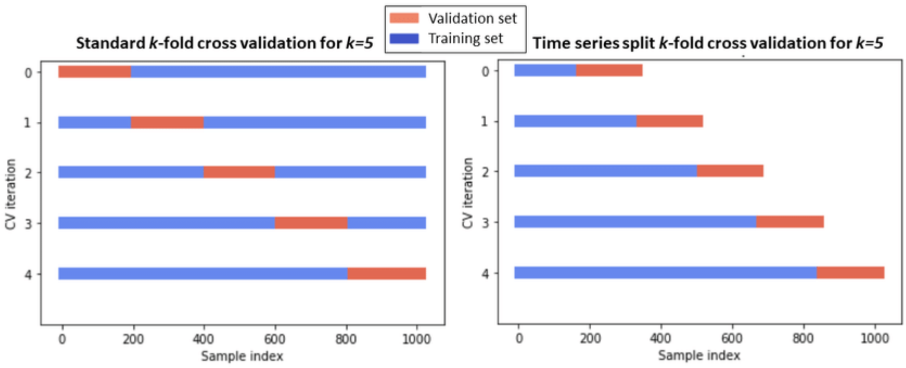

Figure 2: Time series vs Standard k-fold cross validation data splitting schemes.

unbiased categorical forecast performance metric that takes into account the number of correct random forecasts (True positives by chance + True negatives by chance). For highly unbalanced datasets, the Heidke Skill Score converges to the Threat Score, a performance metric often used to evaluate weather forecasting models in China as mentioned in Section 3.3. performance of our models will be compared with a series of benchmarks. Namely, numerical weather prediction forecasts from Harmonie-Arome, and the best-performing machine learning model configuration from Castillo-Botón et al. (2022). That is, the gradient boosted decision trees with oversampling of the minority fog class.

5 Project Plan

While parts of the project might move and be completed before/after their assigned times, these are the initial timelines for different parts of the project:

Exploratory data analysis / Research

- Ethics Form [Week 1]
- Import datasets from Met Eireann and any external [Week 1]
- Data preprocessing/cleaning [Week 1-2]
- Exploratory data analysis [Week 2-4]
- Time series analysis [Week 3-4]
- Fog climatology table [Week 5]
- Cluster analysis [Week 6]
- Fog persistence analysis [Week 5-6]

Modelling

- Replicating model in benchmark paper [Week 7-8]
- Feature engineering [Week 9]
- Variable importance for fog predictions [Week 10]

- Experiments with data preprocessing and hyperparameter tuning [Week 10-11]
- Build final model [Week 12]
- Evaluate final model against benchmarks [Week 12-13]
- Create charts/visualisations for the report [Week 13]

Write-up

- Final Report [Week 12+]

We expect to carry out various forms of data analysis and data processing over the first seven weeks of the semester, with the latter half of the semester focused on building ML models and carrying out experiments to achieve the best results. We plan on taking notes throughout the entire semester, but we will start crafting the final report after the semester ends. Below we attach our proposed Gantt chart.

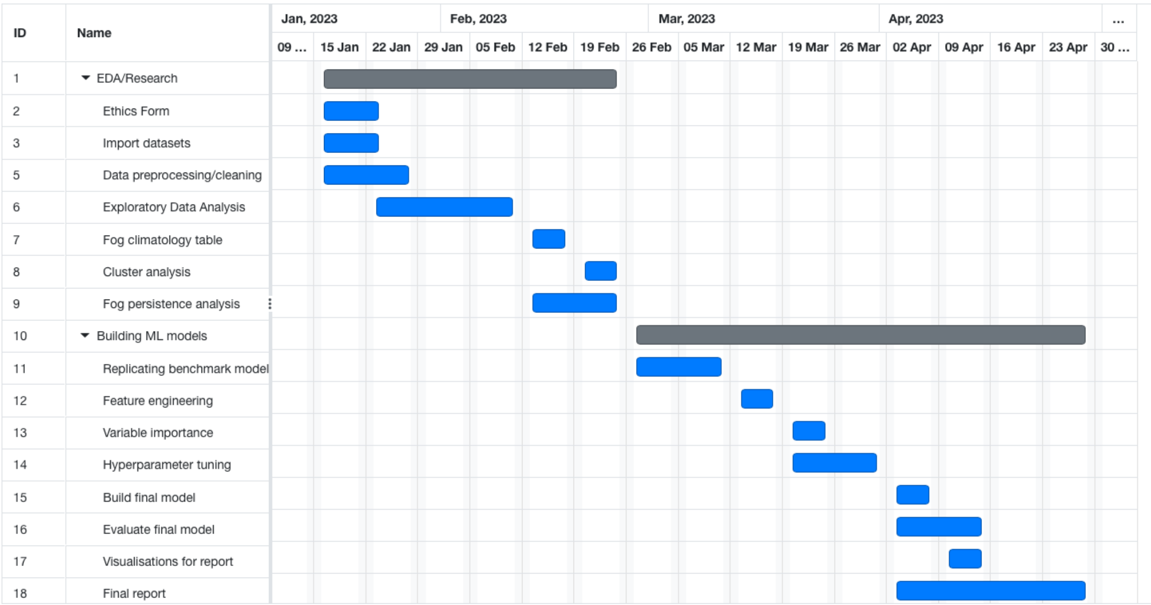

Figure 3: Gantt Chart of our project plan.

References

Belo-Pereira, M. & Santos, J. A. (2016), 'A persistent wintertime fog episode at Lisbon airport (Portugal): performance of ECMWF and AROME models', *Meteorological Applications* **23**(3), 353–370. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/met.1560.
URL: *https://onlinelibrary.wiley.com/doi/abs/10.1002/met.1560*

Bendix, J. (2002), 'A satellite-based climatology of fog and low-level stratus in Germany and adjacent areas', *Atmospheric Research* **64**(1), 3–18.
URL: *https://www.sciencedirect.com/science/article/pii/S0169809502000753*

Bengtsson, L., Andrae, U., Aspelien, T., Batrak, Y., Calvo, J., Rooy, W. d., Gleeson, E., Hansen-Sass, B., Homleid, M., Hortal, M., Ivarsson, K.-I., Lenderink, G., Niemelä, S., Nielsen, K. P., Onvlee, J., Rontu, L., Samuelsson, P., Muñoz, D. S., Subias, A., Tijm, S., Toll, V., Yang, X. & Køltzow, M. (2017), 'The HARMONIE–AROME Model Configuration in the ALADIN–HIRLAM NWP System', *Monthly Weather Review* **145**(5), 1919–1935. Publisher: American Meteorological Society Section: Monthly Weather Review.
URL: *https://journals.ametsoc.org/view/journals/mwre/145/5/mwr-d-16-0417.1.xml*

Bergot, T., Terradellas, E., Cuxart, J., Mira, A., Liechti, O., Mueller, M. & Nielsen, N. W. (2007), 'Intercomparison of Single-Column Numerical Models for the Prediction of Radiation Fog', *Journal of Applied Meteorology and Climatology* **46**(4), 504–521. Publisher: American Meteorological Society Section: Journal of Applied Meteorology and Climatology.
URL: *https://journals.ametsoc.org/view/journals/apme/46/4/jam2475.1.xml*

Boneh, T., Weymouth, G. T., Newham, P., Potts, R., Bally, J., Nicholson, A. E. & Korb, K. B. (2015), 'Fog Forecasting for Melbourne Airport Using a Bayesian Decision Network', *Weather and Forecasting* **30**(5), 1218–1233. Publisher: American Meteorological Society Section: Weather and Forecasting.
URL: *https://journals.ametsoc.org/view/journals/wefo/30/5/waf-d-15-0005$_1$.xml*

Castillo-Botón, C., Casillas-Pérez, D., Casanova-Mateo, C., Ghimire, S., Cerro-Prada, E., Gutierrez, P. A., Deo, R. C. & Salcedo-Sanz, S. (2022), 'Machine learning regression and classification methods for fog events prediction', *Atmospheric Research* **272**, 106157.
URL: *https://www.sciencedirect.com/science/article/pii/S0169809522001430*

Cornejo-Bueno, S., Casillas-Pérez, D., Cornejo-Bueno, L., Chidean, M. I., Caamaño, A. J., Cerro-Prada, E., Casanova-Mateo, C. & Salcedo-Sanz, S. (2021), 'Statistical Analysis and Machine Learning Prediction of Fog-Caused Low-Visibility Events at A-8 Motor-Road in Spain', *Atmosphere* **12**(6), 679. Number: 6 Publisher: Multidisciplinary Digital Publishing Institute.
URL: *https://www.mdpi.com/2073-4433/12/6/679*

Cornejo-Bueno, S., Casillas-Pérez, D., Cornejo-Bueno, L., Chidean, M. I., Caamaño, A. J., Sanz-Justo, J., Casanova-Mateo, C. & Salcedo-Sanz, S. (2020), 'Persistence Analysis and Prediction of Low-Visibility Events at Valladolid Airport, Spain', *Symmetry* **12**(6), 1045. Number: 6 Publisher: Multidisciplinary Digital Publishing Institute.
URL: *https://www.mdpi.com/2073-8994/12/6/1045*

Dutta, D. & Chaudhuri, S. (2015), 'Nowcasting visibility during wintertime fog over the airport of a metropolis of India: decision tree algorithm and artificial neural network approach', *Natural Hazards* **75**(2), 1349–1368.
URL: *https://doi.org/10.1007/s11069-014-1388-9*

Fabbian, D., Dear, R. d. & Lellyett, S. (2007), 'Application of Artificial Neural Network Forecasts to Predict Fog at Canberra International Airport', *Weather and Forecasting* **22**(2), 372–381. Publisher: American Meteorological Society Section: Weather and Forecasting.
URL: *https://journals.ametsoc.org/view/journals/wefo/22/2/waf980$_1$.xml*

Fernández-González, S., Bolgiani, P., Fernández-Villares, J., González, P., García-Gil, A., Suárez, J. C. & Merino, A. (2019), 'Forecasting of poor visibility episodes in the vicinity of Tenerife Norte Airport', *Atmospheric Research* **223**, 49–59.
URL: *https://www.sciencedirect.com/science/article/pii/S0169809519301462*

Huang, H. & Zhang, G. (2017), 'Case Studies of Low-Visibility Forecasting in Falling Snow With WRF Model', *Journal of Geophysical Research: Atmospheres* **122**(23), 12,862–12,874. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/2017JD026459.
URL: *https://onlinelibrary.wiley.com/doi/abs/10.1002/2017JD026459*

Kamangir, H., Collins, W., Tissot, P., King, S. A., Dinh, H. T. H., Durham, N. & Rizzo, J. (2021), 'FogNet: A multiscale 3D CNN with double-branch dense block and attention mechanism for fog prediction', *Machine Learning with Applications* **5**, 100038.
URL: *https://www.sciencedirect.com/science/article/pii/S2666827021000190*

Kim, B.-Y., Cha, J. W., Chang, K.-H. & Lee, C. (2022), 'Estimation of the Visibility in Seoul, South Korea, Based on Particulate Matter and Weather Data, Using Machine-learning Algorithm', *Aerosol and Air Quality Research* **22**(10), 220125. Publisher: Taiwan Association for Aerosol Research.
URL: *https://aaqr.org/articles/aaqr-22-03-oa-0125*

Koziara, M. C., Renard, R. J. & Thompson, W. J. (1983), 'Estimating Marine Fog Probability Using a Model Output Statistics Scheme', *Monthly Weather Review* **111**(12), 2333–2340. Publisher: American Meteorological Society Section: Monthly Weather Review.
URL: *https://journals.ametsoc.org/view/journals/mwre/111/12/1520-0493$_1$983$_1$11$_2$333$_e$mfpua$_{20c}$o$_2$.xml*

Lafore, J. P., Stein, J., Asencio, N., Bougeault, P., Ducrocq, V., Duron, J., Fischer, C., Héreil, P., Mascart, P., Masson, V., Pinty, J. P., Redelsperger, J. L., Richard, E. & Vilà-Guerau de Arellano, J. (1998), 'The Meso-NH Atmospheric Simulation System. Part I: adiabatic formulation and control simulations', *Annales Geophysicae* **16**(1), 90–109. Publisher: Copernicus GmbH.
URL: *https://angeo.copernicus.org/articles/16/90/1998/*

Launch of Ireland's high resolution ensemble-based forecasting system - Met Éireann - The Irish Meteorological Service (n.d.).
URL: *https://www.met.ie/irelands-first-high-resolution-ensemble-based-forecasting-system*

Marzban, C., Leyton, S. & Colman, B. (2007), 'Ceiling and Visibility Forecasts via Neural Networks', *Weather and Forecasting* **22**(3), 466–479. Publisher: American Meteorological Society Section: Weather and Forecasting.
URL: *https://journals.ametsoc.org/view/journals/wefo/22/3/waf994$_1$.xml*

Miao, K.-c., Han, T.-t., Yao, Y.-q., Lu, H., Chen, P., Wang, B. & Zhang, J. (2020), 'Application of LSTM for short term fog forecasting based on meteorological elements', *Neurocomputing* **408**, 285–291.
URL: *https://www.sciencedirect.com/science/article/pii/S0925231220304884*

NWP in Met Éireann (2011).
URL: *https://www.met.ie/science/numerical-weather-prediction/operational-nwp-in-met-eireann*

Roberts, B., Gallo, B. T., Jirak, I. L. & Clark, A. J. (2019), 'The High Resolution Ensemble Forecast (HREF) system: Applications and Performance for Forecasting Convective Storms'. Archive Location: world Publisher: Earth and Space Science Open Archive Section: Meteorology.
URL: *http://www.essoar.org/doi/10.1002/essoar.10501462.1*

Román-Cascón, C., Steeneveld, G. J., Yagüe, C., Sastre, M., Arrillaga, J. A. & Maqueda, G. (2016), 'Forecasting radiation fog at climatologically contrasting sites: evaluation of statistical methods and WRF', *Quarterly Journal of the Royal Meteorological Society* **142**(695), 1048–1063. _eprint: https://rmets.onlinelibrary.wiley.com/doi/pdf/10.1002/qj.2708.
URL: *http://onlinelibrary.wiley.com/doi/abs/10.1002/qj.2708*

Román-Cascón, C., Yagüe, C., Sastre, M., Maqueda, G., Salamanca, F. & Viana, S. (2012), Observations and WRF simulations of fog events at the Spanish Northern Plateau, *in* 'Advances in Science and Research', Vol. 8, Copernicus GmbH, pp. 11–18. ISSN: 1992-0628 Issue: 1.
URL: *https://asr.copernicus.org/articles/8/11/2012/*

Román-Cascón, C., Yagüe, C., Steeneveld, G.-J., Morales, G., Arrillaga, J. A., Sastre, M. & Maqueda, G. (2019), 'Radiation and cloud-base lowering fog events: Observational analysis and evaluation of WRF and HARMONIE', *Atmospheric Research* **229**, 190–207.
URL: *https://www.sciencedirect.com/science/article/pii/S0169809519303515*

Salcedo-Sanz, S., Piles, M., Cuadra, L., Casanova-Mateo, C., Caamaño, A. J., Cerro-Prada, E. & Camps-Valls, G. (2021), 'Long-term persistence, invariant time scales and on-off intermittency of fog events', *Atmospheric Research* **252**, 105456.
URL: *https://www.sciencedirect.com/science/article/pii/S0169809521000089*

Steeneveld, G. J., Ronda, R. J. & Holtslag, A. A. M. (2015), 'The Challenge of Forecasting the Onset and Development of Radiation Fog Using Mesoscale Atmospheric Models', *Boundary-Layer Meteorology* **154**(2), 265–289.
URL: *https://doi.org/10.1007/s10546-014-9973-8*

Stolaki, S., Haeffelin, M., Lac, C., Dupont, J. C., Elias, T. & Masson, V. (2015), 'Influence of aerosols on the life cycle of a radiation fog event. A numerical and observational study', *Atmospheric Research* **151**, 146–161.
URL: *https://www.sciencedirect.com/science/article/pii/S0169809514001951*

US Department of Commerce, N. (n.d.), 'Dew Point vs Humidity'. Publisher: NOAA's National Weather Service.
URL: *https://www.weather.gov/arx/why$_d$ewpoint$_v$s$_h$umidity*

Vorndran, M., Schütz, A., Bendix, J. & Thies, B. (2022), 'Current Training and Validation Weaknesses in Classification-Based Radiation Fog Nowcast Using Machine Learning Algorithms', *Artificial Intelligence for the Earth Systems* **1**(2). Publisher: American Meteorological Society Section: Artificial Intelligence for the Earth Systems.
URL: *https://journals.ametsoc.org/view/journals/aies/1/2/AIES-D-21-0006.1.xml*

WMO (n.d.), 'Fog compared with Mist'.
URL: *https://cloudatlas.wmo.int/fog-compared-with-mist.html*

Wu, J., Fu, C., Zhang, L. & Tang, J. (2012), 'Trends of visibility on sunny days in China in the recent 50 years', *Atmospheric Environment* **55**, 339–346.
URL: *https://www.sciencedirect.com/science/article/pii/S1352231012002786*

Zhou, B., Du, J., Gultepe, I. & Dimego, G. (2012), 'Forecast of Low Visibility and Fog from NCEP: Current Status and Efforts', *Pure and Applied Geophysics* **169**(5), 895–909.
URL: *https://doi.org/10.1007/s00024-011-0327-x*