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Wavelets in Neural Network

SUPERVISED RESEARCH EXPOSITION

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Introduction

- The atmosphere is a very complex system and understanding the atmosphere is key to anyone in a science-related field really – not just to meteorologists
- Atmospheric stability is determined by temperature and humidity structure, and these meteorological variables are critical inputs for weather prediction models
- It is important to agriculture, water companies, electric companies, FedEx, and other related traveling companies of the like

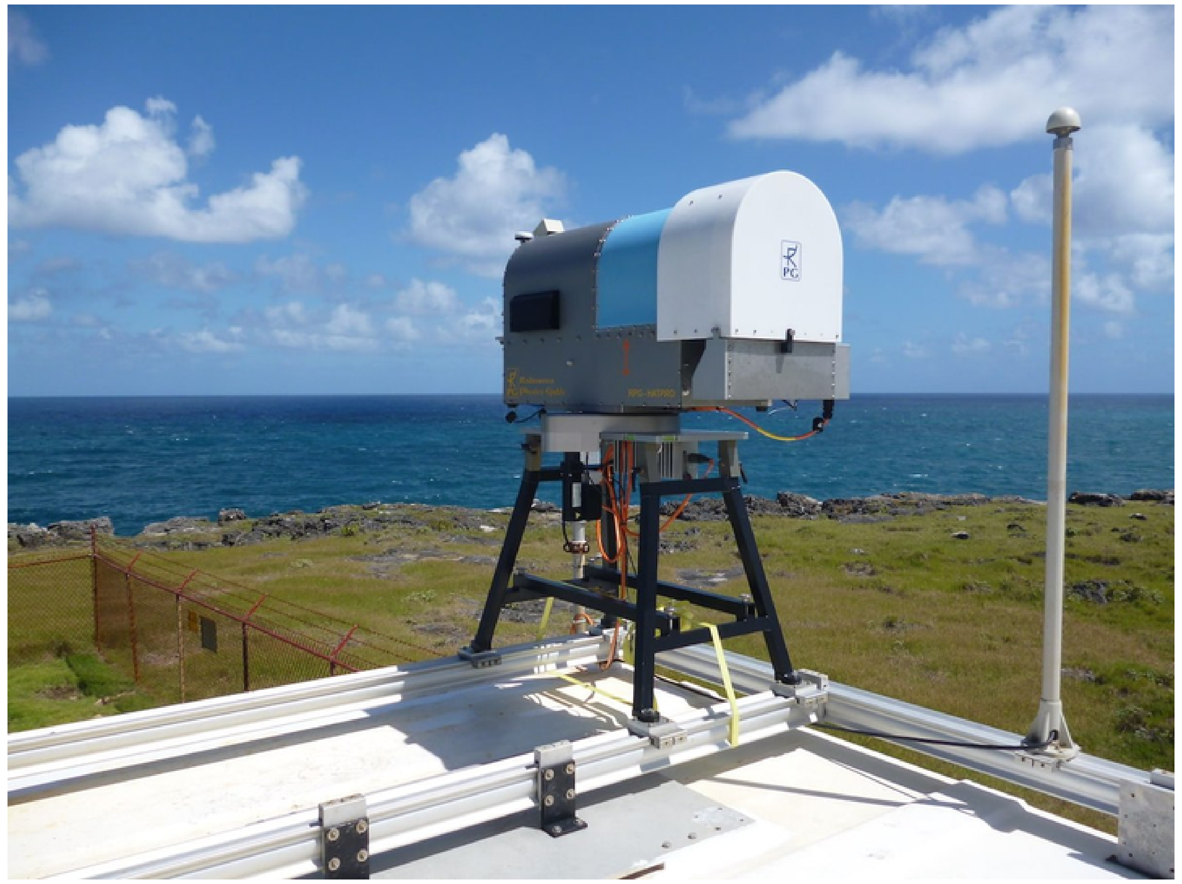
Introduction

- The global radiosonde network currently provides atmospheric vertical profiles of temperature and humidity
- The observations are constrained by their expense and poor temporal resolution which is insufficient to capture the diurnal change of the atmospheric structure, despite the high accuracy of the data obtained from this source

Source: https://www.collinsdictionary.com/dictionary/english/radiosonde

Introduction

- A more contemporary method that may be used to collect crucial information on weather profiles in the lower part of the atmosphere is a ground-based Microwave Radiometer (MWR)
- The fundamental measurement obtained from MWR are brightness temperature Tb at different microwave frequencies



Source: *https://en.wikipedia.org/wiki/Microwave_radiometer*

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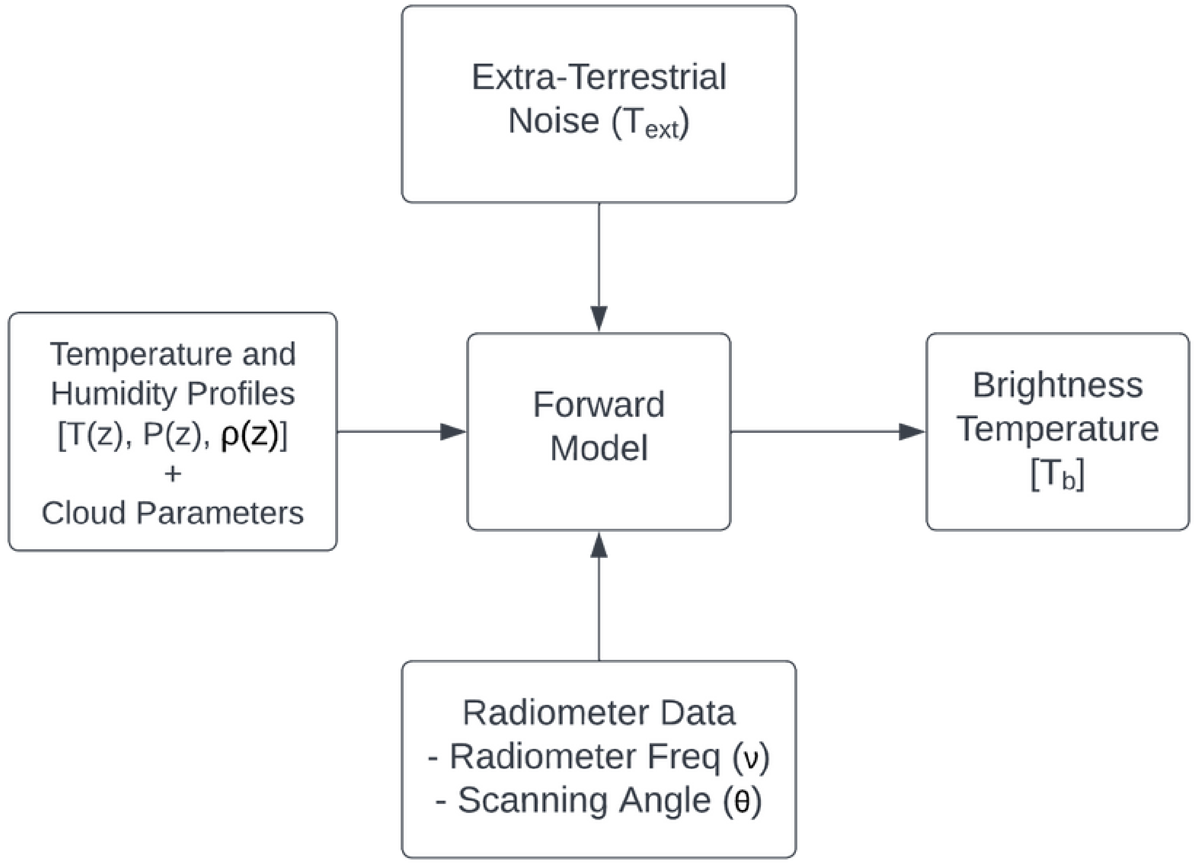
Forward Model

- The computation of Tb are mainly comprises Radiative Transfer Equations and Weighting Functions which are dependent on Atmospheric Absorption and the Radiometric Channel Frequency
- In the frequency range from 20 to 200 GHz, water vapour, oxygen, and cloud liquid are the main sources of atmospheric emission and absorption



Source: https://www.researchgate.net/publication/271660882_Evaluation_of_brightness_temperature_from_a_forward_model_of_ground-based_microwave_radiometer

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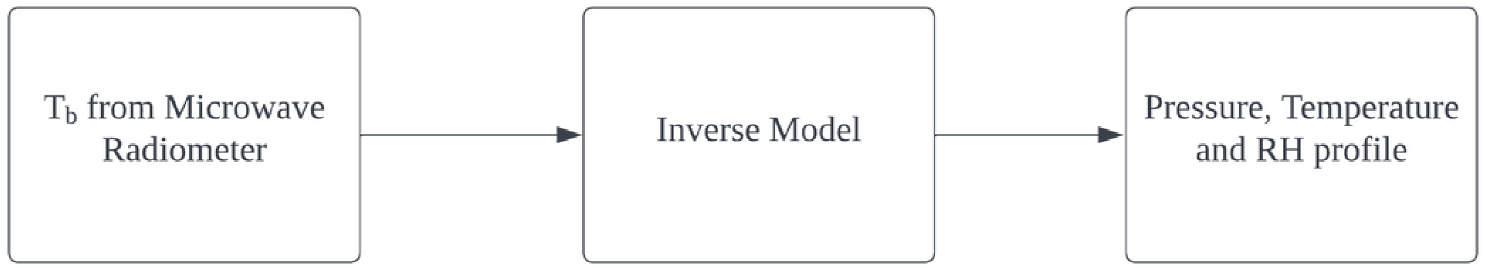
Inverse Model

- We are interested in the Inverse model of the Microwave Radiometer (MWR) which retrieves atmospheric profiles from measured brightness temperature
- There is no closed function that directly extracts the atmospheric profile from the MWR measurements and thus we need to approximate it



Aim

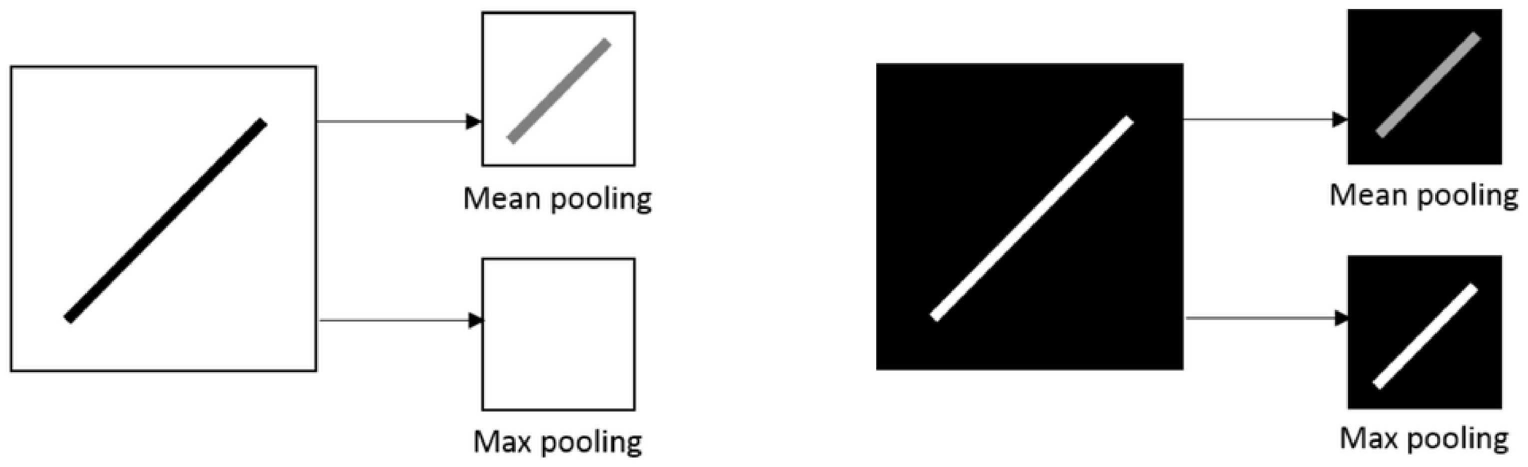
In this study, we shall be attempting to build an Inverse Model to retrieve the atmospheric profile from the MWR data utilizing wavelets in our Algorithm

Literature Review

Wavelet Pooling for Convolutional Neural Network

Travis Williams, Robert Li

- Pooling is a critical layer in CNN which helps in feature reduction and provides robustness against noise
- Max pooling and Average pooling are the most common strategies employed for this purpose



SHORTCOMINGS OF MAX AND AVERAGE POOLING

Source: https://openreview.net/forum?id=rkhlb8lCZ

Wavelet Pooling for Convolutional Neural Network

Travis Williams, Robert Li

- The authors propose the use of discrete wavelet transform in combination with downsampling to provide pooling output
- Their suggested solution provides better results than max and average pooling in around 2/3rd of the datasets and performs in respectable range in rest

Retrieval of Temperature and Relative Humidity Profiles from Microwave Radiometer

Xing Yan, Liang Chen, Nana Lou

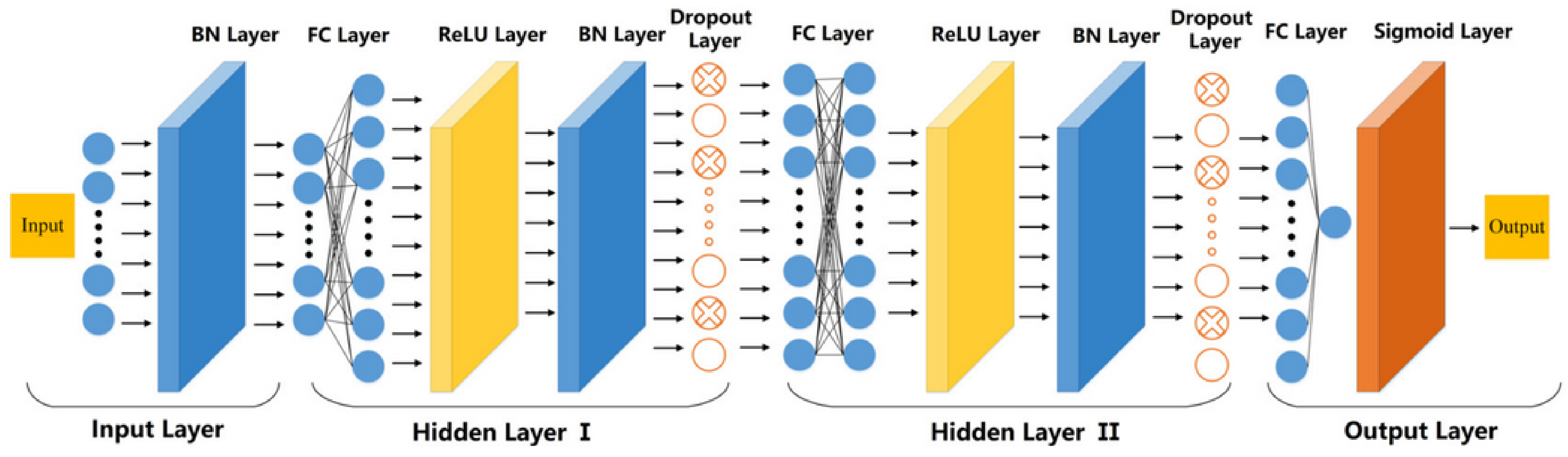
- The research proposed works on similar lines to retrieve atmospheric profiles from MWR data
- Multiple approaches such as XGBoost, Support Vector Machine, Ridge regression, and Multilayer feedforward neural network are deployed by the authors

Source: https://ieeexplore.ieee.org/document/9082142

Retrieval of Temperature and Relative Humidity Profiles from Microwave Radiometer

Xing Yan, Liang Chen, Nana Lou

- The BRNN which is a feedforward neural network proposed in the study is found to perform best for retrieval of the atmospheric profile



Source: https://ieeexplore.ieee.org/document/9082142

Proposed Methodology

Proposed Methodology

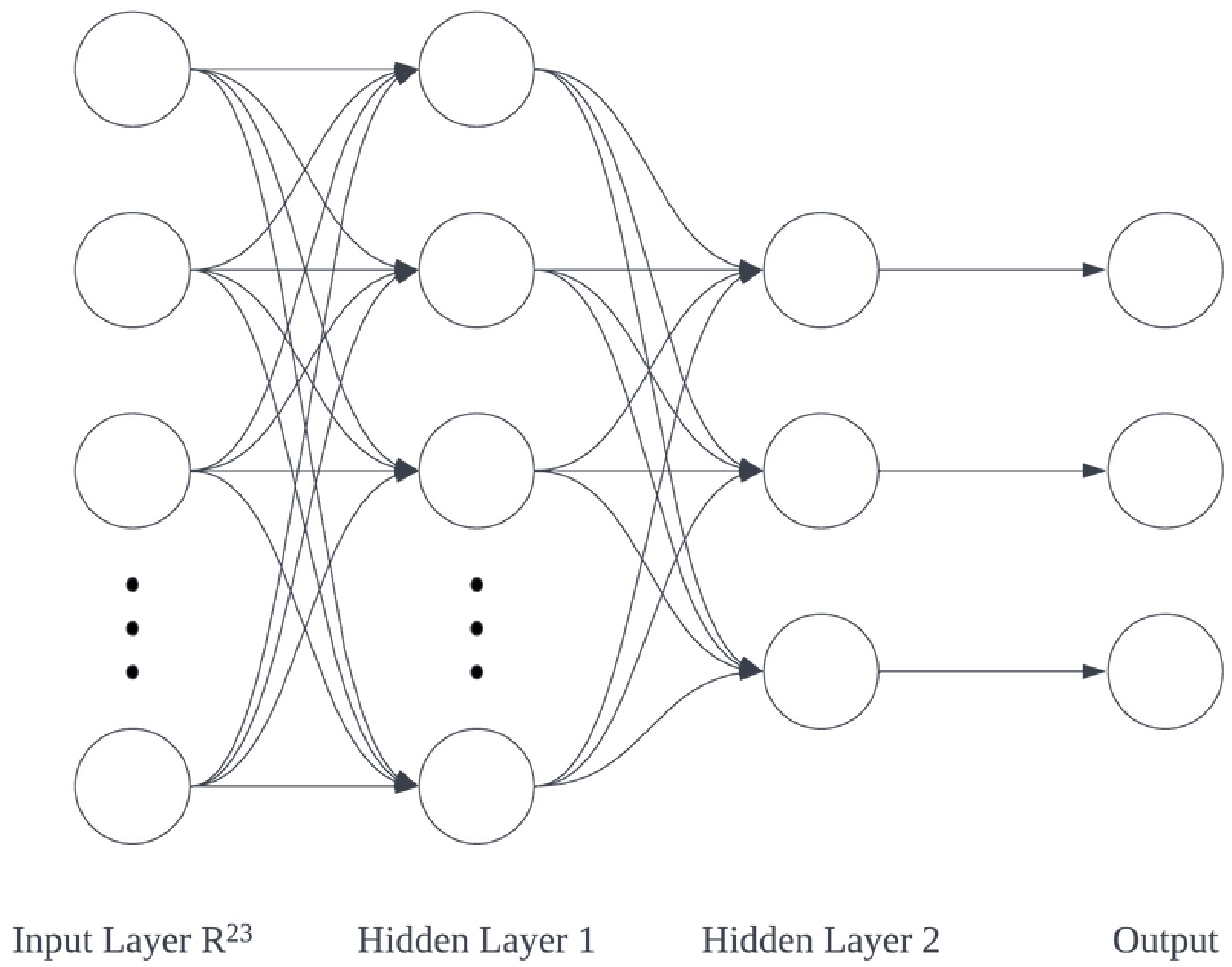
- In the initial duration of the exposition, the proposed hypothesis was to build a model to predict the vertical atmospheric profile using only the MWR channels following the empirical form
  M(y1,y2 . . ,y22) = [p, t, rh]
- Later we proposed a slight modification adding height as a parameter into the model with the final model as
  M(h, y1, y2, ..., y22) = [p, t, rh]

Linear Regression

- Trying to understand Linear Correlation
- y=b0+b1x1+b2x2+....b23x23 where xi=height+22 channel data

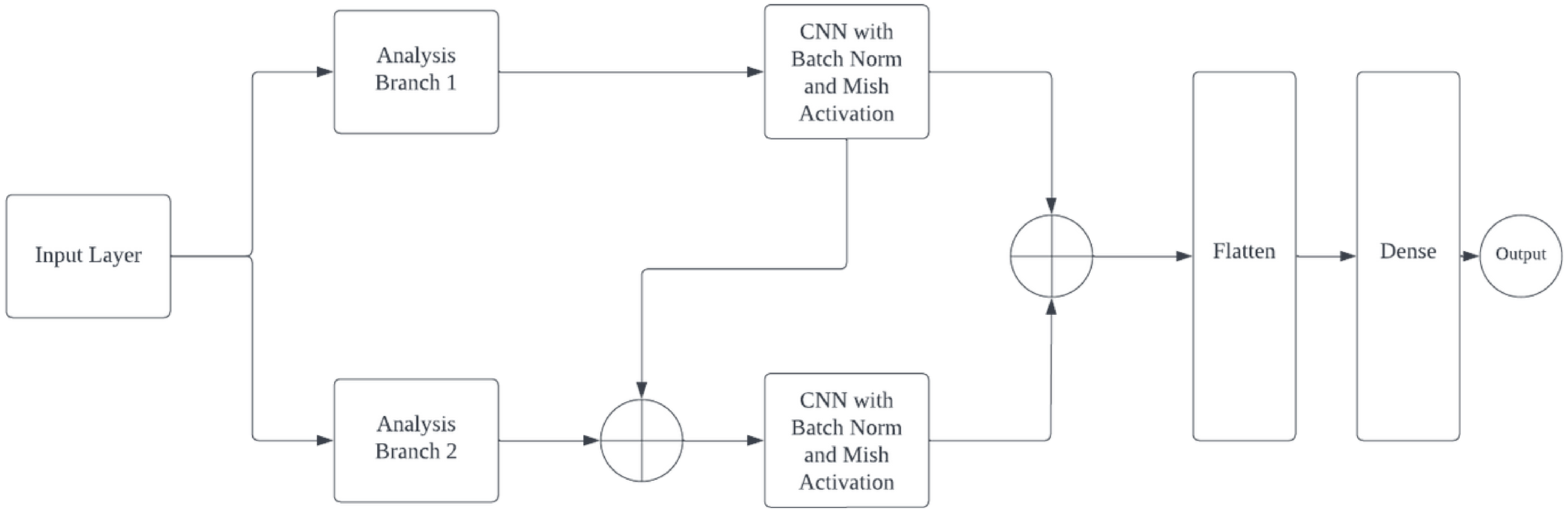
Multilayer Perceptron Neural Network

- The model -2 hidden layers with 23 neurons(first layer) and 3 neurons(second layer)
- 552 +72 = 624 trainable parameters
- relu, sigmoid, mish and wavelets like morlet and mexican hat(admissible wavelets)



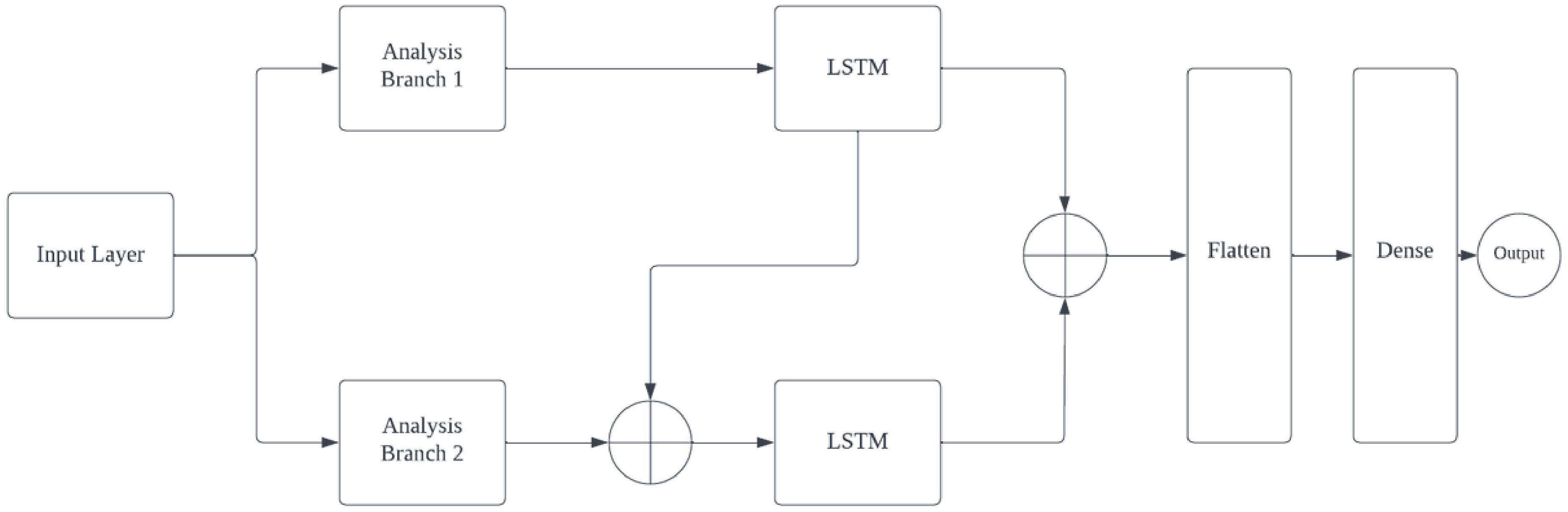
Wavelet Convolutional Neural Network

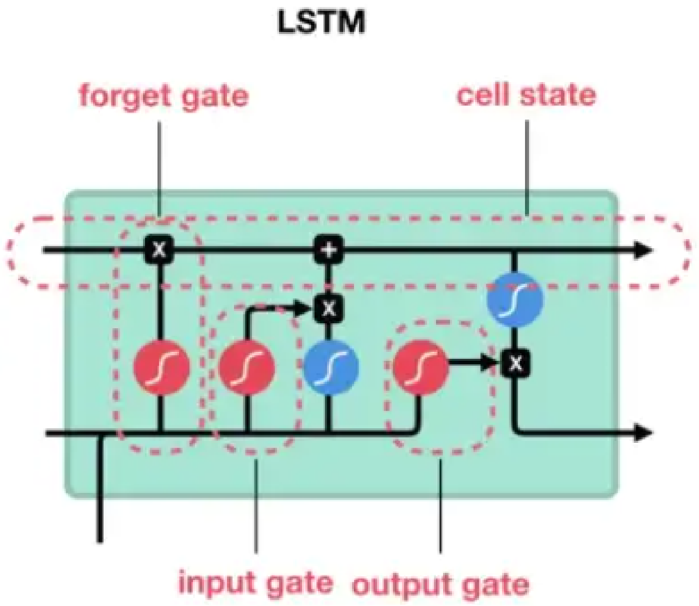
- Level-1 decomposition
- Trained using cnn with 624 trainable parameters
- Mish activation and batch normalization
- Used a flatten and dense layer in conjugation to get back 3 outputs



Modified Wavelet Convolutional Neural Network (MWCNN)

- LSTM's in place of CNN's to improve the fit of highly volatile Relative Humidity data
- The MWCNN is trained separately on K bands and V bands for predicting temperature and humidty

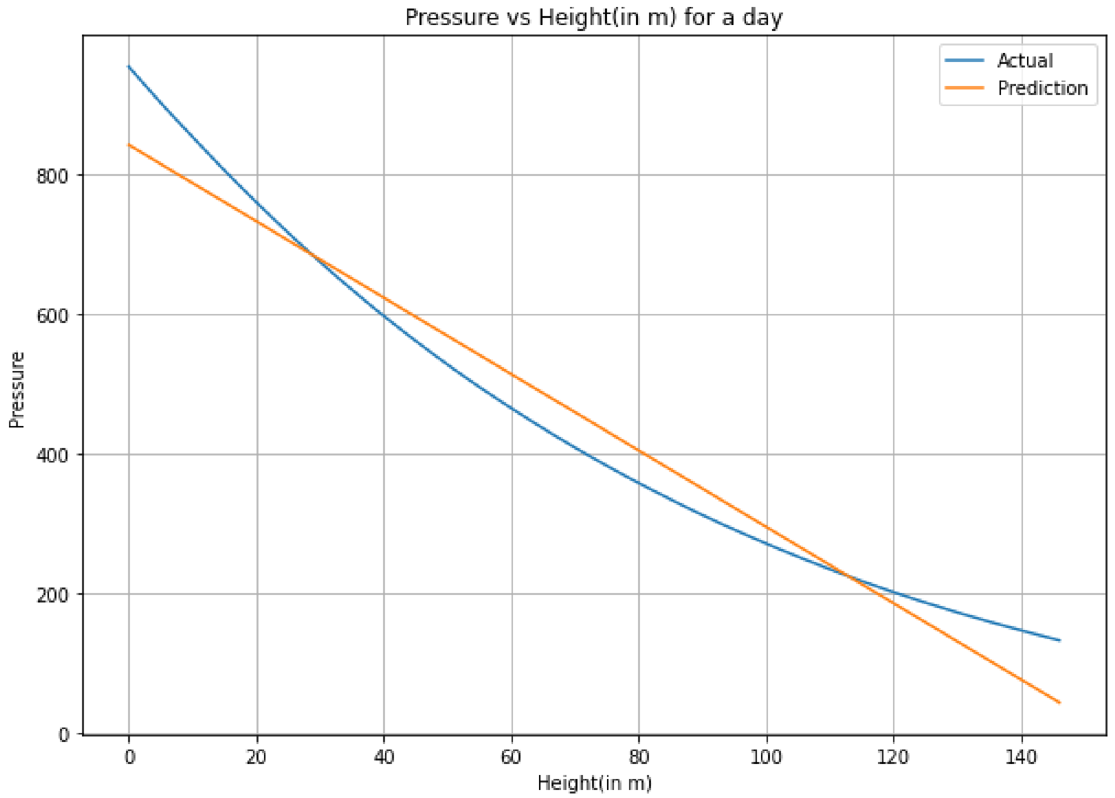


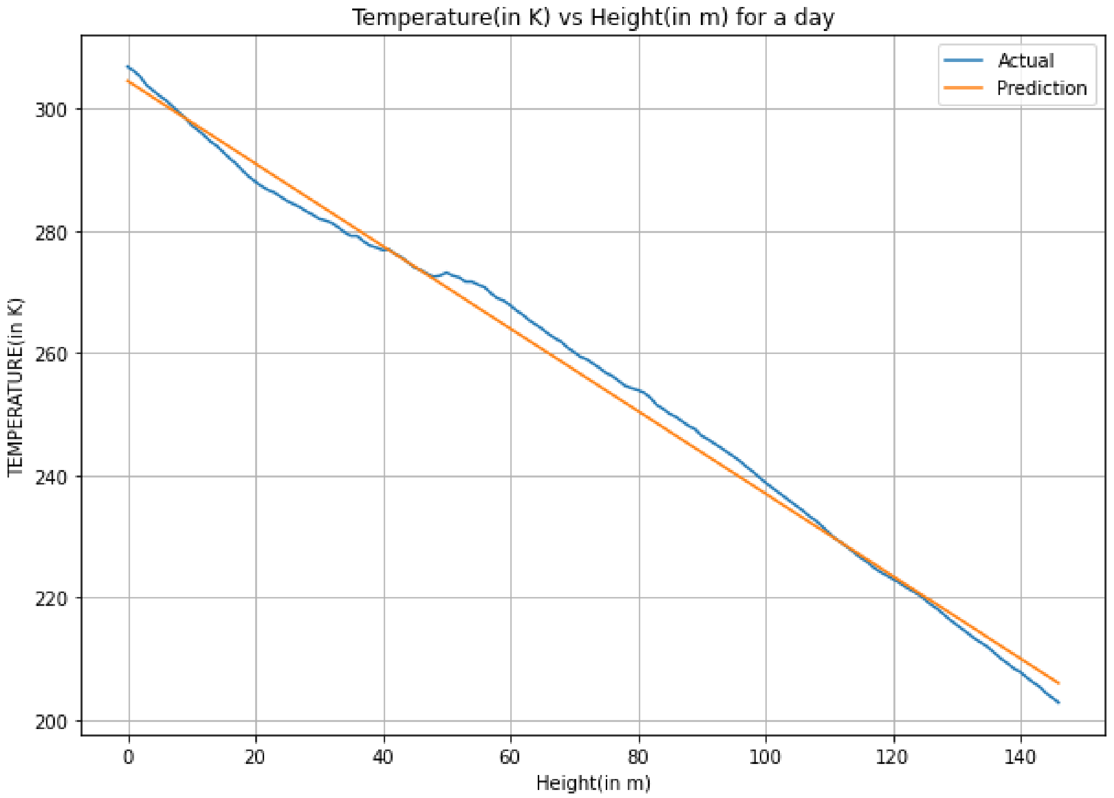


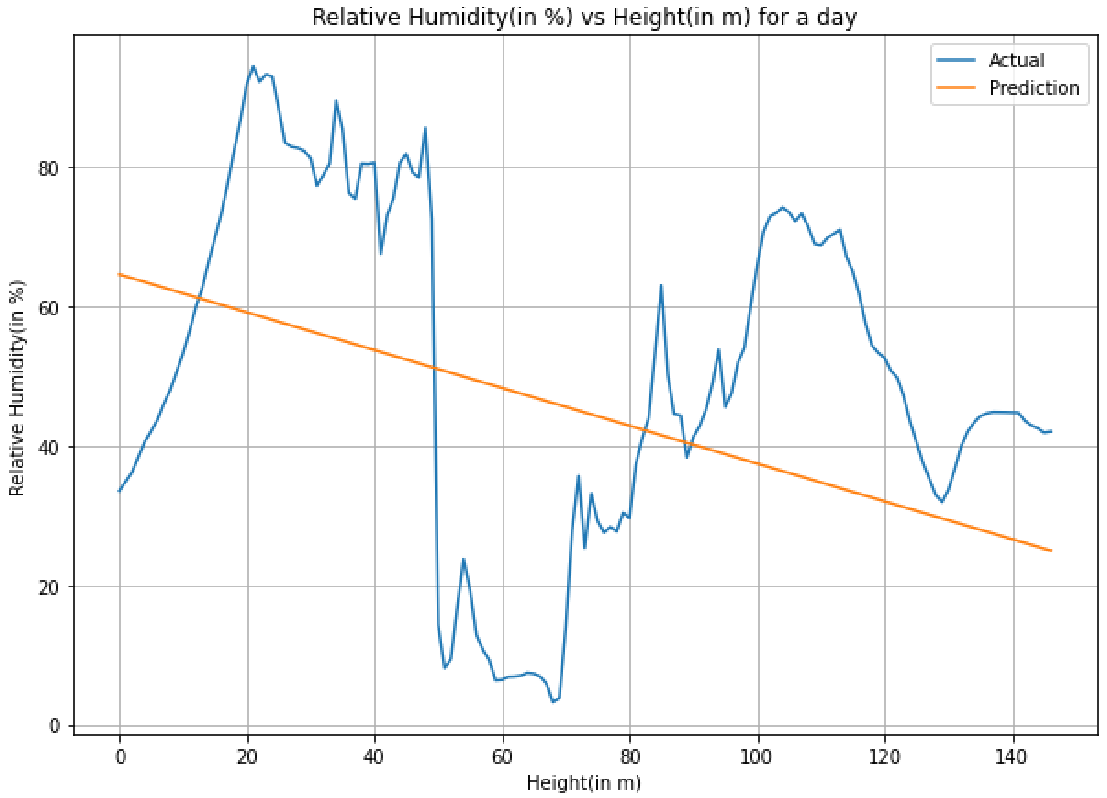
Source:Michael Phi,https://towardsdatascience.com/illustrated-guide-to-lstms-and-gru-s-a-step-by-step-explanation-44e9eb85bf21

Results

Linear Regression





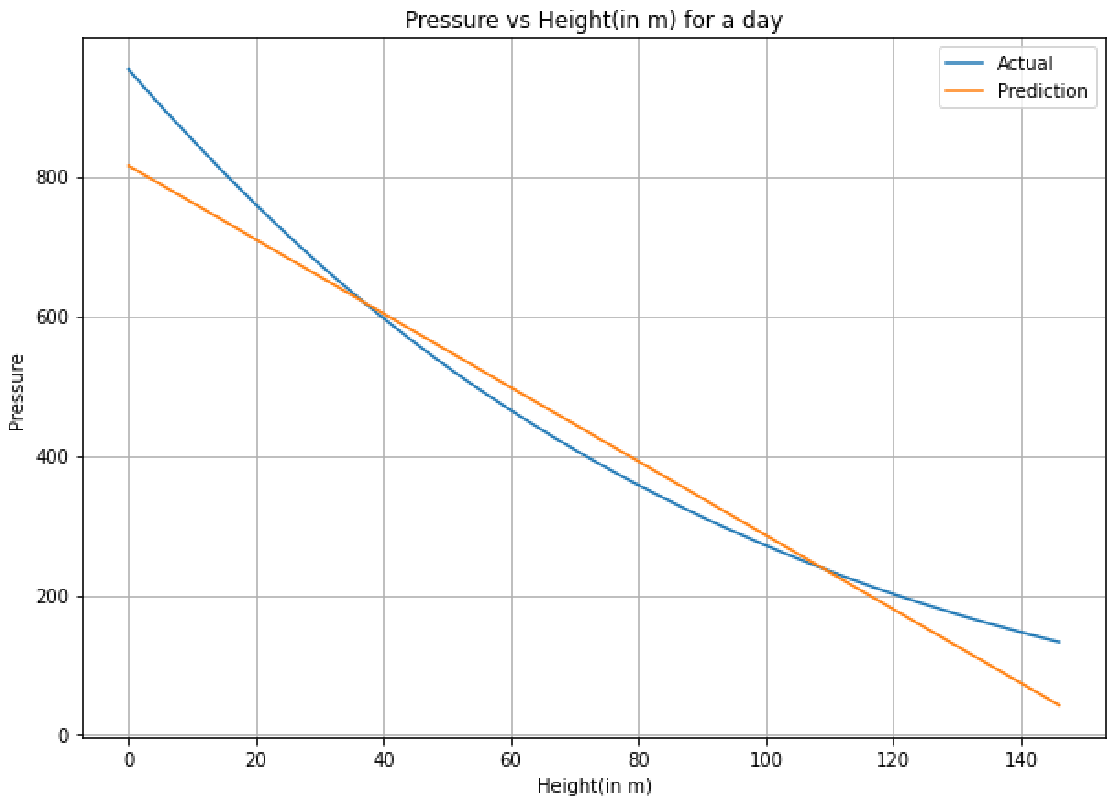


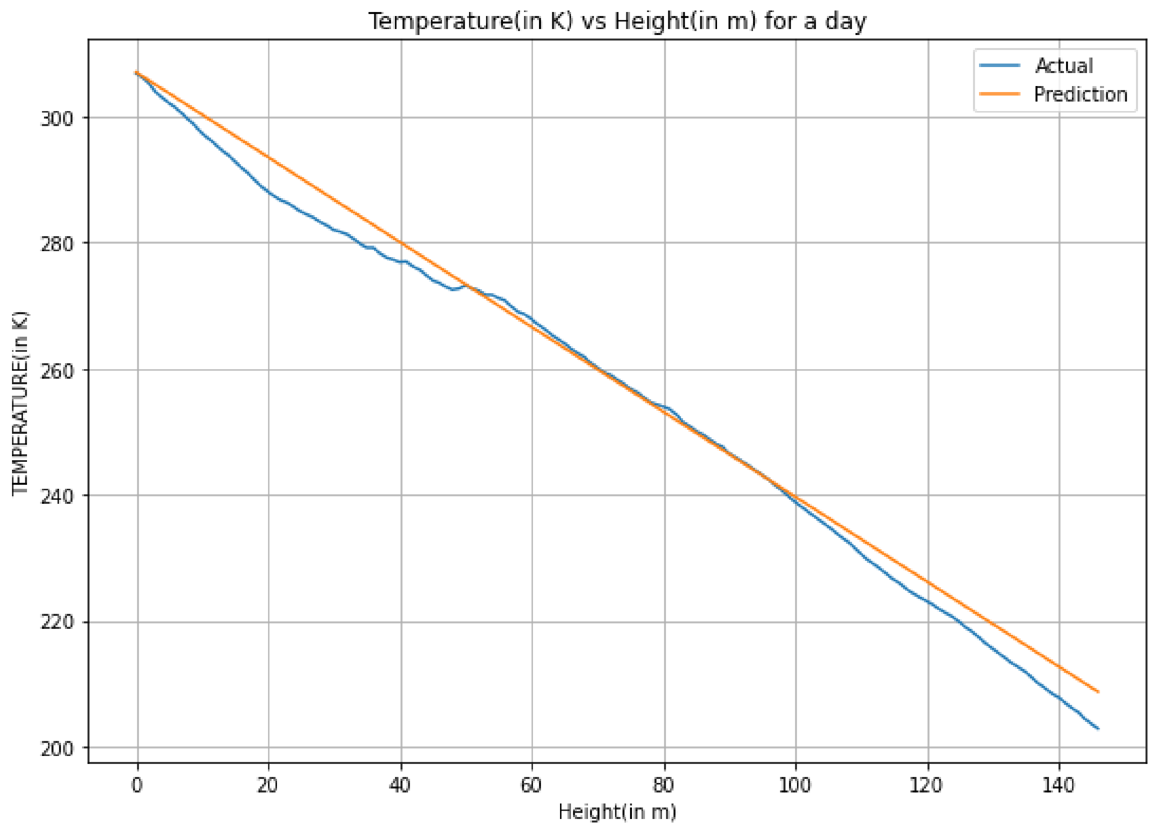
MAE: 39.497
PE: 0.123

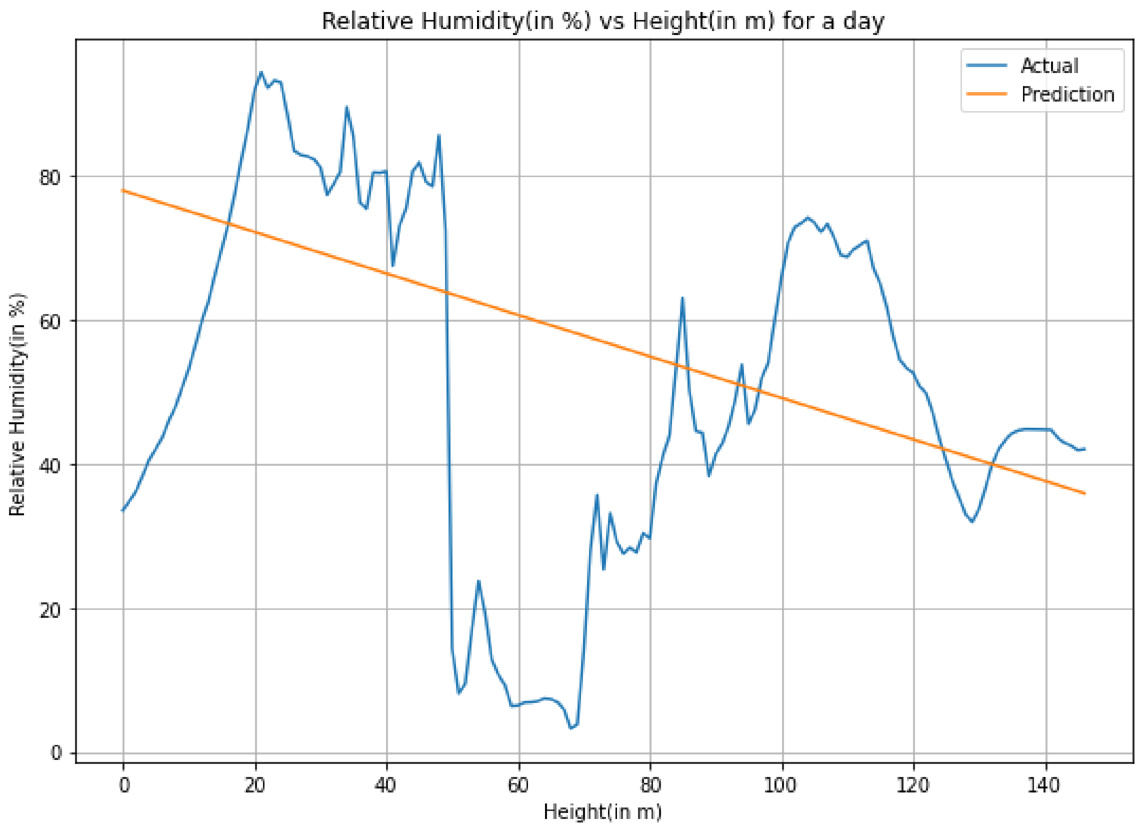
MAE: 2.262
PE: 0.0091

MAE: 14.365
PE: 0.4949

Multilayer Perceptron Neural Network







MAE: 38.558
PE: 0.1180

MAE: 2.590
PE: 0.0105

MAE: 14.553
PE: 0.5467

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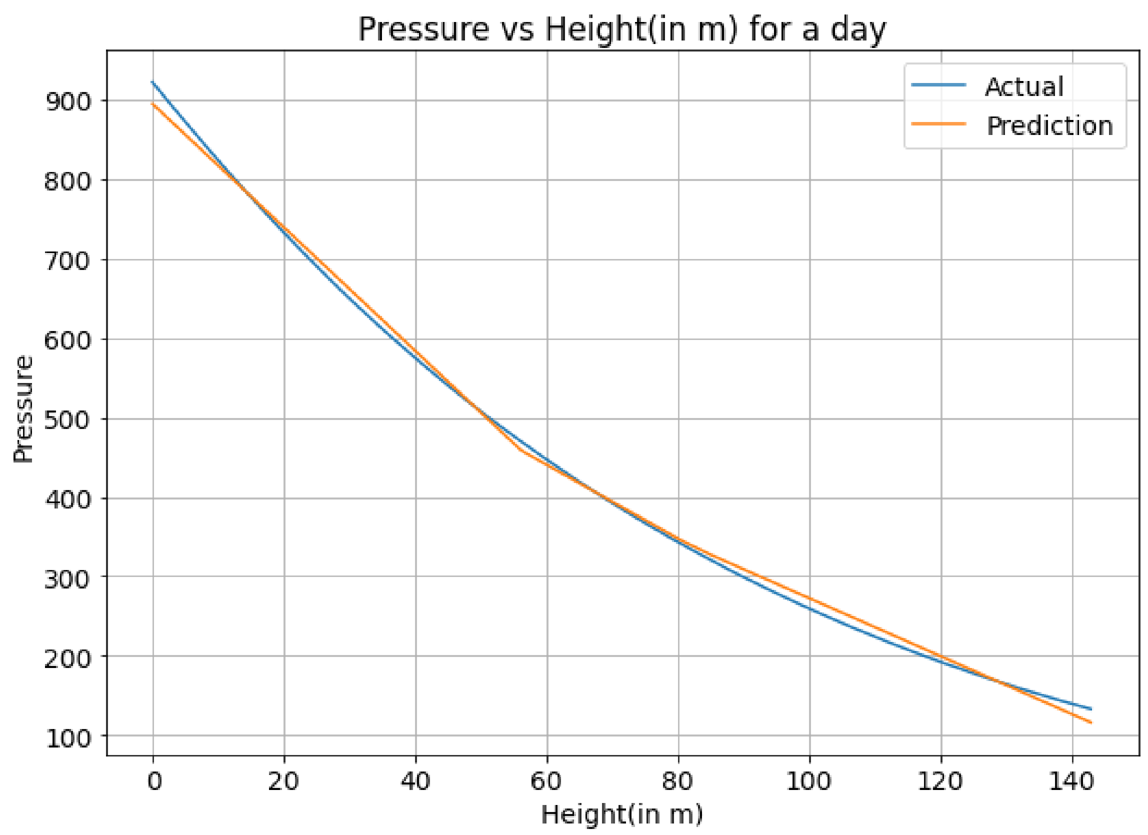
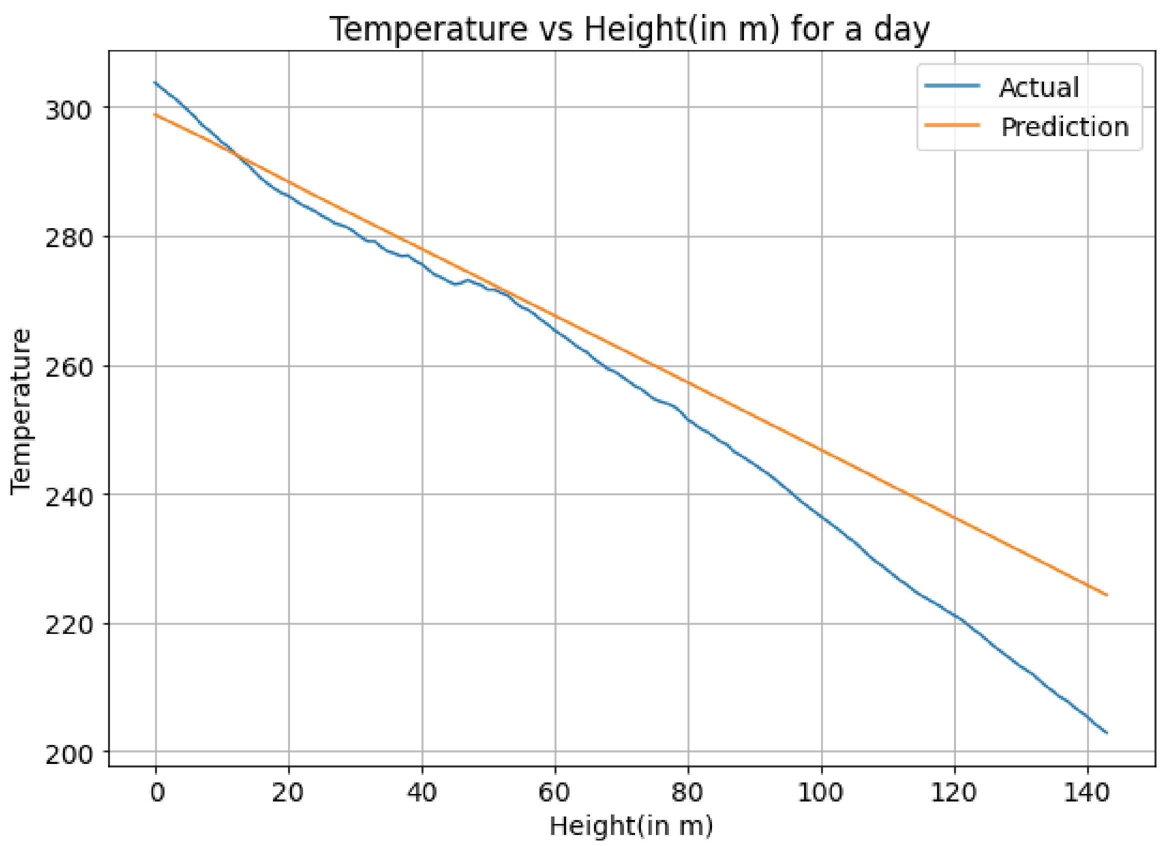
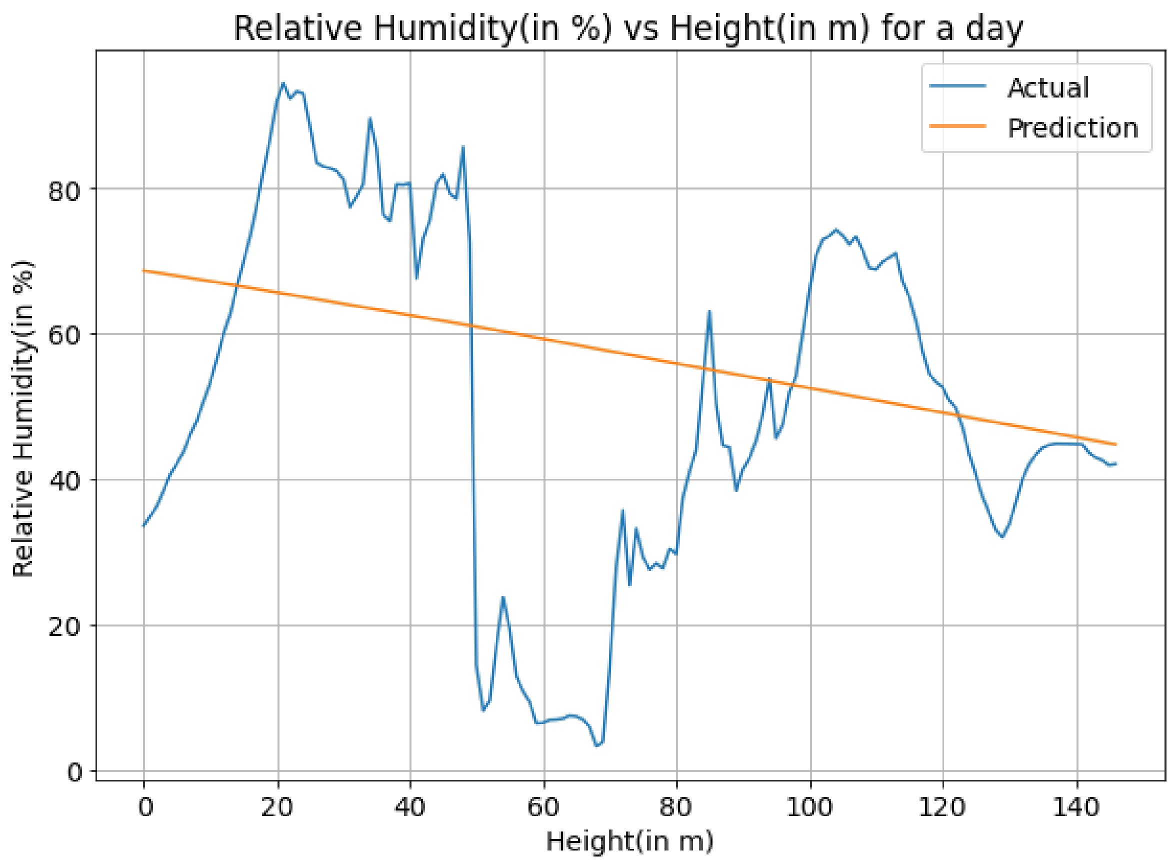
Wavelet Convolutional Neural Network





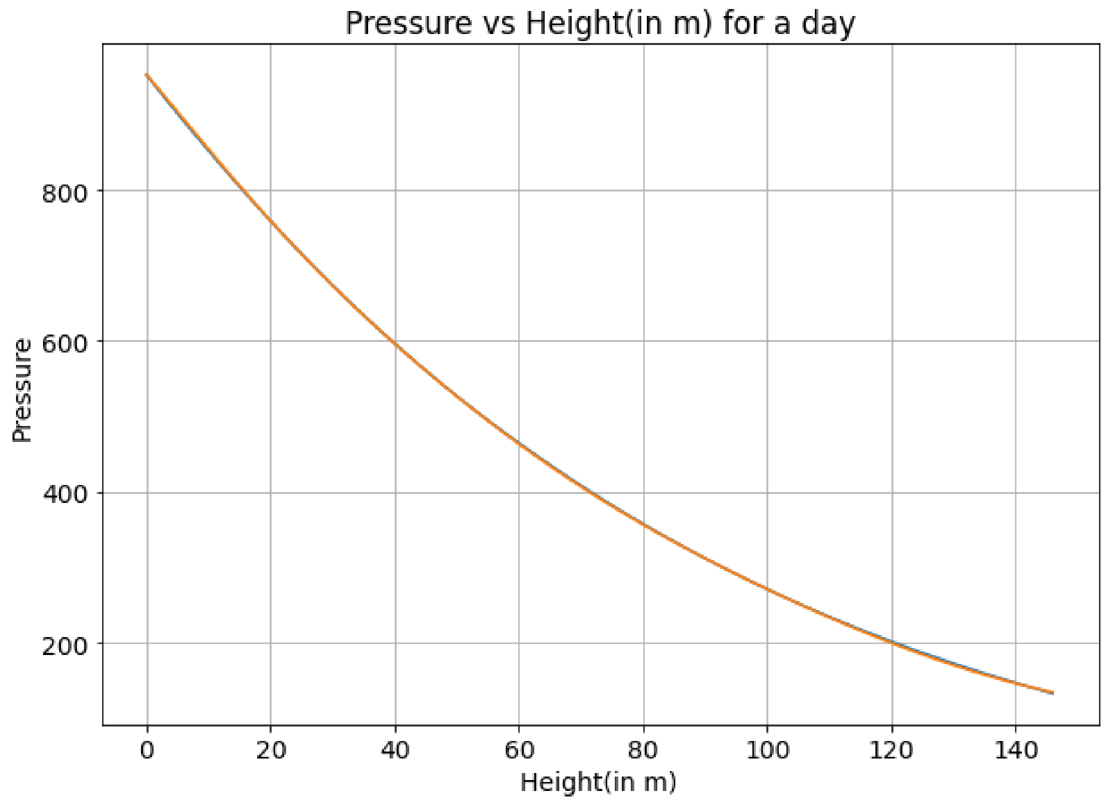


MAE: 15.232
PE: 0.0401

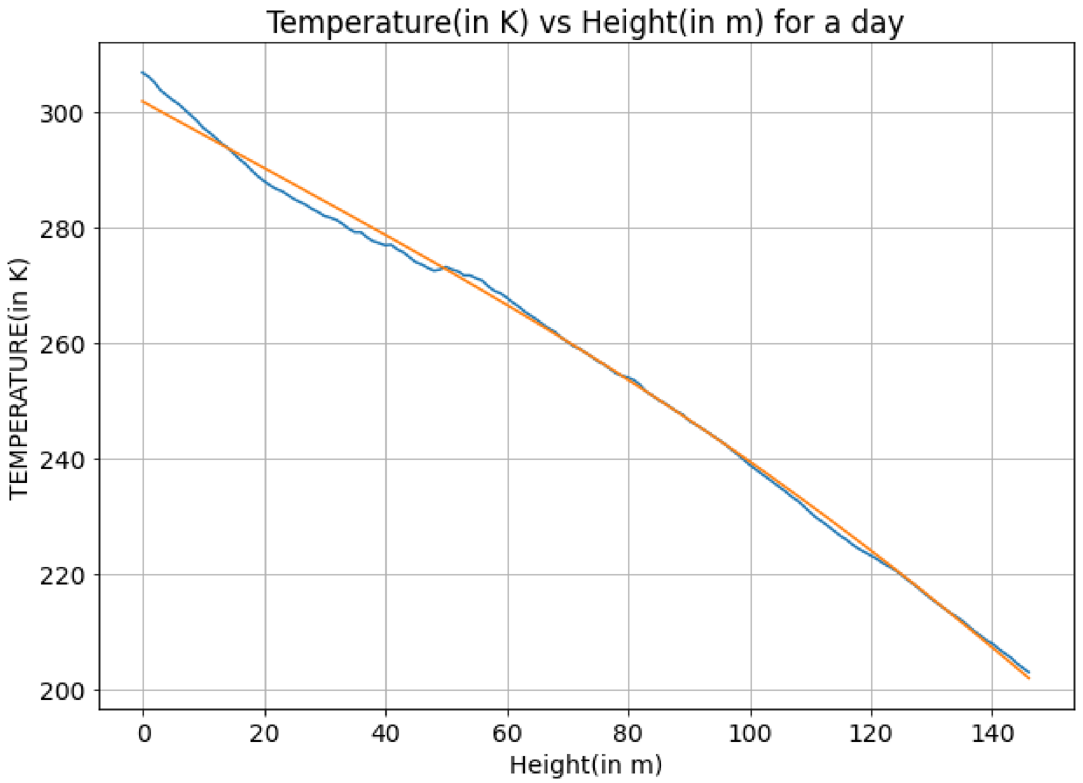
MAE: 6.950
PE: 0.0296

MAE: 15.098
PE: 0.5653

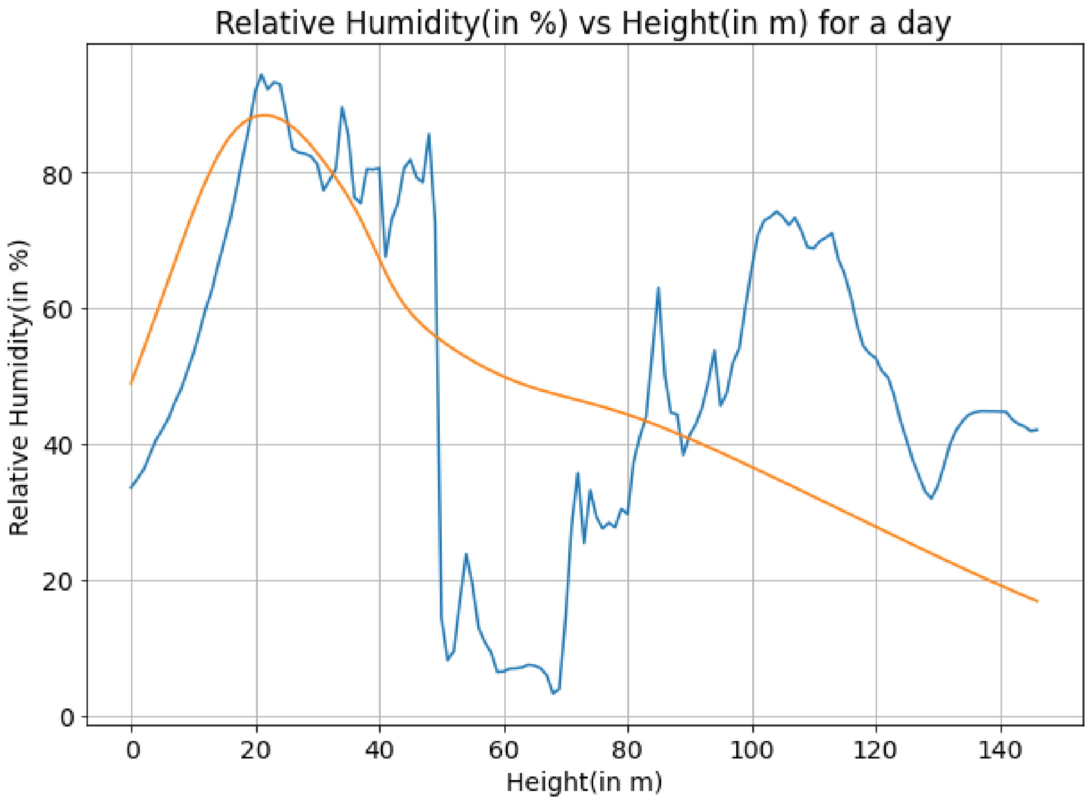
Modified Wavelet Convolutional Neural Network



MAE: 1.275
PE: 0.0037

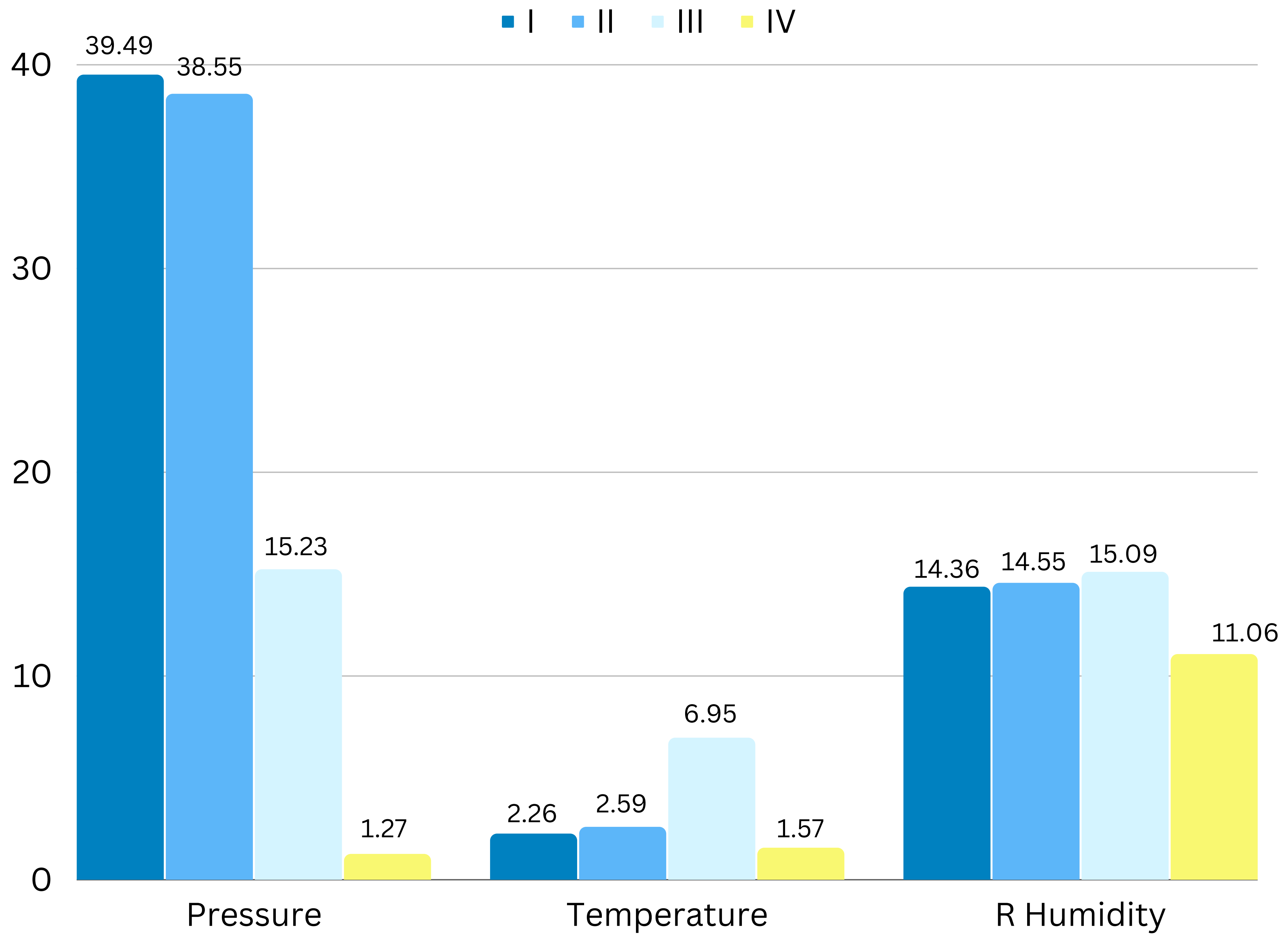


MAE: 1.578
PE: 0.0061

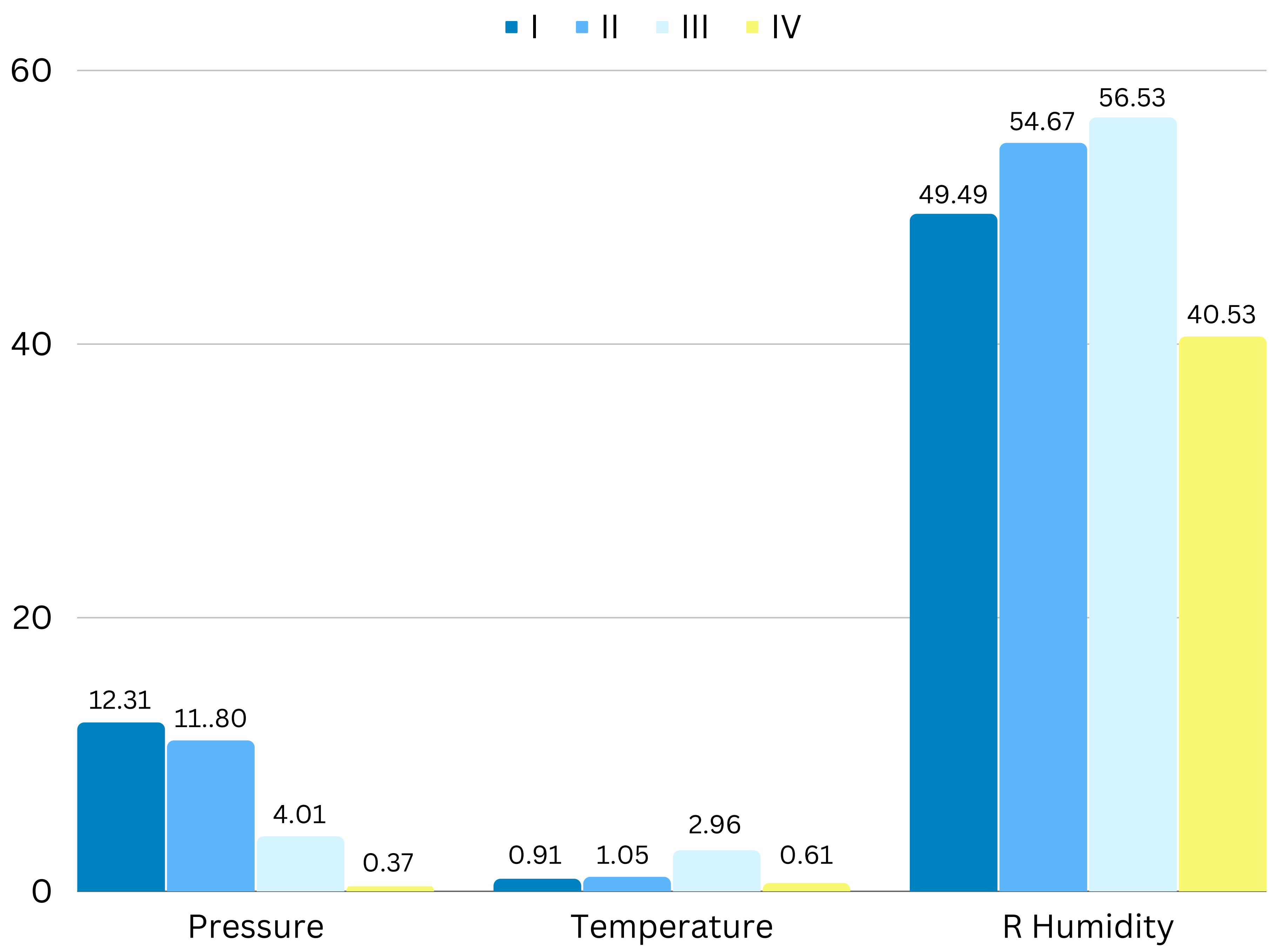


MAE: 11.063
PE: 0.4053

Mean Absolute Error Comparison



Percentage Error Comparison



Comparison with existing Literature

- The mean error for modeling temperature by SAMEER was at 3.3, K Ramesh in his publication* was 1.08, and that of Xing Yan* was 1.29 and ours was at 1.57
- For relative humidity ANFIS model varied between 5-20%, and that of BRNN was 11.72% as compared to 40.53% from MWCNN

*: *Adaptive neuro-fuzzy inference system for temperature and humidity profile retrieval from microwave radiometer observations*
**: *Retrieval of Temperature and Relative Humidity Profiles from Microwave Radiometer.*

CONCLUSION AND FUTURE SCOPE

- In this study, we have demonstrated the use of wavelets in conjunction with deep learning to retrieve atmospheric profiles; using a sparse network to emphasize more on wavelet transform
- The results of our proposed model show considerable improvement over other compared methods in all the parameters

CONCLUSION AND FUTURE SCOPE

- Potential for improving the model especially in for prediction of relative humidity
- Getting a deeper understanding of the relation we are trying to establish between the two wavelet sub-bands
- Exploring different wavelets and higher level of decompositions
- Architecture of the model also has much potential to be refined

Thank you for listening!