UNT UNIVERSITY OF NORTH TEXAS

"Analyzing the Impact of Urban Air Quality on Public Health: A Data Mining and Machine Learning Approach"

Executive Summary

- Analyzed the impact of environmental factors on Health Risk Score using machine learning techniques to support public health initiatives.

Models Implemented

  - **Linear Regression:** Provided a baseline understanding of the relationship between environmental factors and health risk.
  - **Decision Tree:** Captured non-linear interactions, with Model 2 preferred for its complex pattern identification.
  - **Random Forest:** Enhanced prediction accuracy by averaging multiple trees, reducing overfitting.
  - **Auto Neural Network:** Explored deep non-linear relationships but had higher error in comparison to other models.

- Heat Index and Humidity emerged as primary drivers of Health Risk Score, highlighting the health impact of high temperatures and air moisture.
- **Best Model:** The Linear Regression model with stepwise selection achieved the lowest average squared error (0.013), offering the most accurate and interpretable results.

Findings underline the importance of monitoring heat and humidity for health risk management in urban planning and healthcare policies.

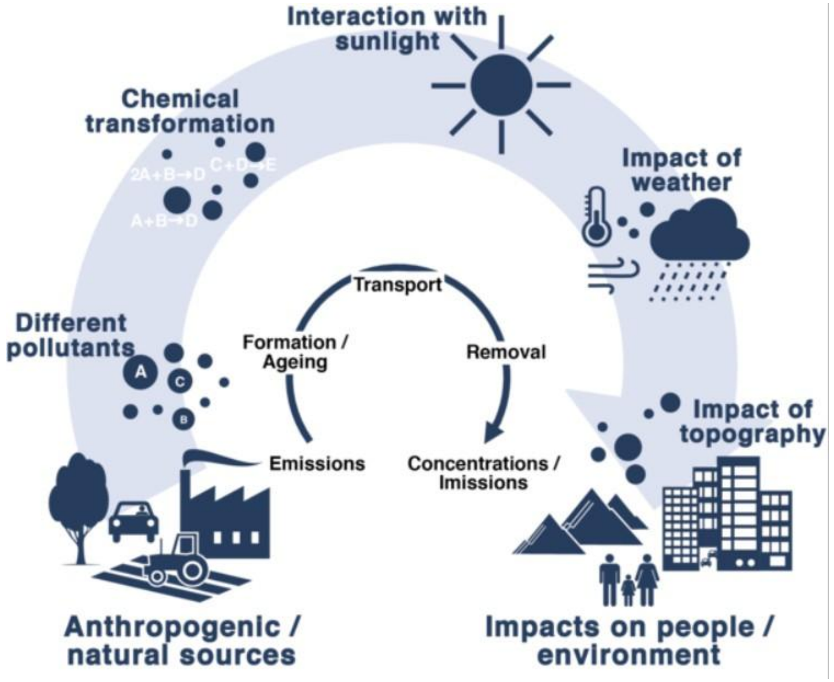
Project Motivation/Background

Why We Chose This Project

- Increasing awareness and concern about how urban air quality impacts health, especially in dense, industrialized cities.
- This project allows us to leverage data mining and machine learning to uncover patterns and trends in air quality data and correlate them with health impacts.
- Results can inform policy-making, health advisories, and urban planning for healthier cities.

Importance of the Project

- With growing urban populations, the importance of monitoring and managing air pollution is crucial for sustainable living.
- Poor air quality is linked to several health issues, including respiratory diseases, cardiovascular problems, and even premature mortality.
- By building predictive models, we aim to proactively address health risks associated with urban air pollution.



Dataset Overview

- ➢ The chosen dataset, **Urban Air Quality and Health Impact Analysis**, contains variables that capture various indicators of air quality—such as pollutant levels (e.g., PM2.5, NO2, O3), weather conditions, and demographic or socioeconomic factors—and links these to health outcomes in urban populations.
- ➢ This dataset allows us to explore the direct and indirect effects of air pollution on public health, making it ideal for predictive modeling in public health and environmental sciences.

The dataset contains 46 columns/variables and a significant number of rows representing various weather and health-related variables.

Predictive Variables:

- **Health_Risk_Score:** Index representing the effects of urban air quality on public health.
- The goal is to predict how air pollutant concentrations affect health based on weather and air quality data.

Category	Variables	Description
Target Variable	Health Risk Score	Quantifies overall health risks based on environmental factors.
Independent Variables		
Weather Attributes	Temperature (Max, Min, Avg, Feels Like), Dew Point, Humidity, Precipitation, Wind Speed, Pressure, Cloud Cover, Visibility and more	Key weather indicators impacting pollutant dispersion and health outcomes.
Additional Fields	Solar Radiation, UV Index, Moon Phase and more	Extra environmental factors for a comprehensive analysis.

Summary Statistics

Class Variables

- **Variable Details:** Each variable has a defined role, number of levels, and mode (most frequent value).
- **Missing Data:** Significant missing values in: preciptype - 622 missing values, stations - 933 missing values
- **Mode:** Shows the most frequent value for each variable (e.g., **City**: "Chicago" - 13.1%).
- **Secondary Mode:** Highlights secondary common values where applicable (e.g., **Day_of_Week**: "Saturday" - 20.5%, "Monday" - 13.9%).

Interval Variables

- **No Missing Values:** All interval variables are complete with no missing data.
- **Statistical Details:**
  - **Mean, Median, Standard Deviation:** Provides insights into central tendency and spread of values.
  - **Skewness:** Most variables have skewness between -3 and +3, indicating minimal skewness and relatively normal distributions.
  - **Range:** Highlights variability with minimum and maximum values across different variables.

Data Role=TRAIN

Data Role	Variable Name	Role	Number of Levels	Missing	Mode	Mode Percentage	Mode2	Mode2 Percentage
TRAIN	City	INPUT	10	0	Chicago	13.10	New York City	11.30
TRAIN	Day_of_Week	INPUT	7	0	Saturday	20.50	Monday	13.90
TRAIN	Is_Weekend	INPUT	2	0	False	66.80	True	33.20
TRAIN	conditions	INPUT	4	0	Clear	56.90	Partially cloudy	36.30
TRAIN	description	INPUT	12	0	Clear conditions throughout the	55.40	Partly cloudy throughout the day	28.90
TRAIN	icon	INPUT	4	0	clear-day	56.90	partly-cloudy-day	36.30
TRAIN	preciptype	INPUT	2	622		62.20	['rain']	37.80
TRAIN	source	INPUT	2	0	fcst	93.30	comb	6.70
TRAIN	stations	INPUT	11	933		93.30	['KORD', 'KMDW', 'F1983', 'KPWK'	1.20

Class Variables Summary

Variable	Role	Mean	Standard Deviation	Non Missing	Missing	Minimum	Median	Maximum	Skewness	Kurtosis
Heat_Index	INPUT	80.19561	6.053805	1000	0	65.51168	78.55225	96.68416	0.367248	-0.40708
Severity_Score	INPUT	3.057743	0.624024	1000	0	1.578048	3.026132	5.158112	0.432824	0.212616
Temp_Range	INPUT	16.4699	5.552785	1000	0	1.676587	16.69407	29.79076	-0.45944	0.120658
cloudcover	INPUT	24.16015	22.43877	1000	0	-4.39913	17.3	101.5813	1.371373	1.394269
datetimeEpoch	INPUT	1.7263E9	374583.4	1000	0	1.7256E9	1.7263E9	1.727E9	0.023845	-6.4719
dew	INPUT	57.26712	9.161517	1000	0	26.26181	58.59698	76.64867	-0.39292	0.04969
feelslike	INPUT	76.32329	8.621361	1000	0	57.74882	75.50661	98.19398	0.200733	-0.95875
feelslikemax	INPUT	85.19538	9.496951	1000	0	62.20641	84.26815	105.0602	0.037509	-0.79648
feelslikemin	INPUT	68.54755	8.365809	1000	0	48.83404	67.84182	89.36985	0.08492	-0.69277
humidity	INPUT	56.78228	16.70867	1000	0	11.75213	58.40587	92.45929	-0.73347	0.549305

Interval Variables Summary

Data Preparation

STEP 1: Initial Data Cleaning
Variable Rejection: Three variables, condition_code, snow_depth, and snow, were identified as containing only 0 values, which provide no analytical value. These variables were rejected during file import in SAS Enterprise Miner.

STEP 2: Handling Missing Values
For variables with missing values, we applied imputation techniques to ensure a complete dataset for analysis.
→ **Tree Surrogate Method:** For class variables with missing values, we used the Tree Surrogate Method to intelligently fill in missing data based on patterns observed in other variables. This approach preserved relationships within the dataset for enhanced model accuracy.

STEP 3: Outlier Treatment
Outlier Detection: Used box plots to identify outliers in significant variables, including **Humidity**, **Dew**, **Temp**, and **UV Index….**
→ **Handling Strategy:** We treated outliers using methods like Imputation and Transformation.

STEP 4: Addressing Non-Normal Distributions
- Applied **log transformations** to a few slightly skewed variables to improve interpretability and ensure model accuracy, particularly for **Linear Regression** and **Neural Networks**.
- **No Transformation is applied to Decision Tree** as it is robust it can handle as splits are created based on data ranges rather than specific values, means outliers do not significantly influence model structure.

We Ensured that the data met assumptions required for effective modeling.

Data Partitioning

- Splitting the data is essential for training **supervised machine learning algorithms**.
- In supervised learning, the model learns from **historical data** (training set), identifying patterns and rules to apply to new, unseen data.

Why is Data Splitting Important?

- It helps **reduce overfitting**, where a model may perform well on training data but poorly on new data.
- Ensures the model's **predictions are reliable** when applied to real-world scenarios.

Data Split for This Project:

By dividing the dataset into different subsets, we can ensure the model **generalizes well** and performs reliably:

- **60% for Training**: The portion of data used to build the model.
- **20% for Validation**: Helps in model tuning and selection.
- **20% for Testing**: Final check on model performance

Data Modelling

Target Variable: Health Risk Score
Type: Continuous
Model Suitability: We selected models that are well-suited for predicting continuous outcomes to ensure accurate health risk predictions.

Chosen Models

1. Linear Regression

- Provides a baseline by modeling linear relationships between predictors and the health risk score.
- Ideal for continuous target variables, offering insights into the direct effects of environmental factors.

2. Decision Tree

- Captures non-linear relationships and interactions among predictors to predict continuous outcomes.
- Well-suited for continuous targets, helping identify key factors impacting health risks.

3. Random Forest

- Ensemble of decision trees that improves accuracy and reduces overfitting for continuous predictions.
- Effective for continuous targets, as it handles feature interactions and variability in complex datasets.

4. Auto Neural Network

- Models complex, non-linear relationships to predict continuous target values.
- Appropriate for continuous outcomes, especially useful for capturing intricate patterns in data.

Model 1 – Linear Regression

We performed regression using different methods to identify the best fit model for predicting health risk.

Model Comparisons:

1. **Regression Model 1 - All Variables**

   R-Squared: 0.9749, **Adjusted R-Squared:** 0.9728

   Not Valid, Contains insignificant variables, which can inflate R-squared values.

2. **Regression Model 2 - Only Significant Variables**

   R-Squared: 0.9702, **Adjusted R-Squared:** 0.9696

   Simplifies the model by focusing on important factors, reducing potential errors.

3. **Regression Model 3 after transformation - Stepwise Selection**

   R-Squared: 0.9728, **Adjusted R-Squared:** 0.9718

   Chosen Model: Stepwise regression due to efficient variable selection.

Why Stepwise Regression?

Model 1 is not valid because of insignificant variables, Between Model 2 and Model 3 - Stepwise Regression has Slightly more R-square Value.

- Automatically selects significant variables, improving interpretability.
- Focuses on key predictors, enhancing model robustness. Eliminates irrelevant variables, generalizing better to new data.
- Minimizes human bias in model selection.

  From all these models we used Regression model 3(stepwise) for model comparison with other models.

MODEL 1

Model Fit Statistics

R-Square	0.9749	Adj R-Sq	0.9728
AIC	-2571.6843	BIC	-2561.3516
SBC	-2360.6317	C(p)	48.0000

MODEL 2

Model Fit Statistics

R-Square	0.9702	Adj R-Sq	0.9696
AIC	-2539.0930	BIC	-2536.5181
SBC	-2481.9329	C(p)	13.0000

MODEL 3

Model Fit Statistics

R-Square	0.9728	Adj R-Sq	0.9718
AIC	-2574.2687	BIC	-2571.9226
SBC	-2477.5362	C(p)	39.3157

Findings from linear regression model

Model Performance

- **R-Squared:** 0.9728, **Adjusted R-Squared:** 0.9718
- Indicates a strong fit, explaining over 97% of the variance in the Health Risk Score.

Important Predictors

- **Heat Index:** Most significant predictor (F Value = 2377.95), suggesting a strong influence on health risk.
- **Humidity** High impact on health risk scores, with F values of 316.39 respectively.
- **Other Influential Variables:** Conditions, Pressure, UV Index, and Wind Speed also show significant effects on health risk.

Influence on Health Risk Score

- **Positive Impact:** Variables like Heat Index and Humidity are associated with increased health risk scores.
- **Negative or Neutral Impact:** Some environmental variables like Visibility and Wind Direction have less influence but still contribute to overall risk assessment.

Regression Equation for Health Risk Score:

Health_Risk_Score = β_0+ 0.7143 * city + 31.4239 * Heat_Index + 0. 6313 * Severity_Score ….+ 0.2811 * windgust

- A one-unit increase in **Heat Index** leads to a **31.42** increase in the Health Risk Score, holding all other variables constant.
- Other factors like **Severity Score**, **Conditions**, and **Dew** have similar effects on Health Risk Score, but their impact is smaller compared to Heat Index

Model 2 – Decision Tree

Decision Tree Model 1: Autonomous Tree with Subtree Assessment

- Automatically created tree using average square error for subtree assessment.
- **Optimal Leaves:** 35
- **Method:** Tree grown by minimizing average square error and pruned to achieve an optimal structure with 35 leaves.

Decision Tree Model 2: Maximum Branches with Three-Way Splits

- Tree model allowing maximum branches with three-way splits.
- **Optimal Leaves:** 50
- **Method:** Provides greater flexibility in splitting, resulting in a deeper structure with more leaves, capturing more complex patterns in the data.

Preferred Model: Decision Tree Model 2

- **Reason:** Captures more intricate patterns with three-way splits and a larger number of leaves, making it better suited for identifying complex relationships in the dataset.

Findings from Decision Tree

The model provides a hierarchical structure that shows the most influential variables in predicting **Health_Risk_Score**.

Top Splitting Variable:

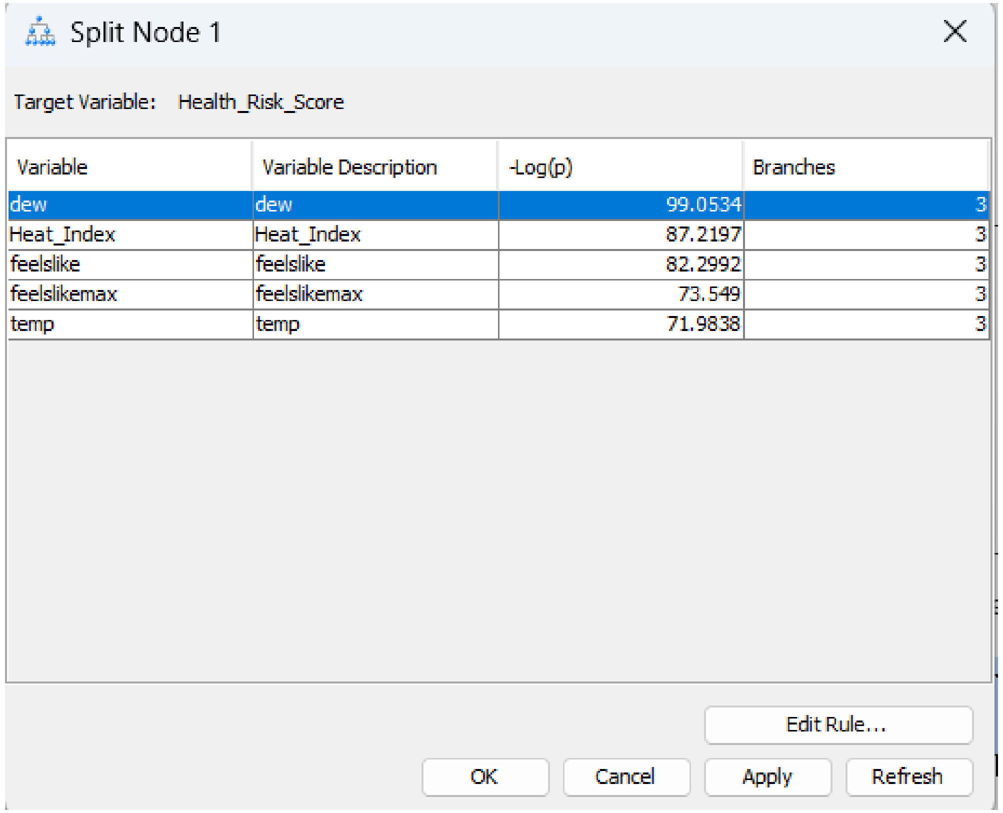
- **Dew**: Primary split variable with highest predictive value, indicating a strong relationship between humidity levels and health risks.

Other Important Predictors:

- **City**: Different cities show distinct health risk profiles, likely due to local pollution and climate conditions.
- **Heat Index and FeelsLike**: Both suggest that perceived temperature and heat stress are key factors impacting health risk.

Influence on Dependent Variable:

- **Dew** has the most significant impact, followed by **City** and **Heat Index**.
- Variables like **FeelsLike** indicate that both actual and perceived temperatures are relevant.



Variable	Variable Description	-Log(p)	Branches
dew	dew	99.0534	3
Heat_Index	Heat_Index	87.2197	3
feelslike	feelslike	82.2992	3
feelslikemax	feelslikemax	73.549	3
temp	temp	71.9838	3

Model 3 – Random Forest

A Random Forest is an ensemble method, combining multiple decision trees to improve predictive performance and reduce overfitting by averaging predictions across many trees.

Created a **Random Forest** model using **average square error** as the evaluation measure on the **validation data**.

Key Findings

- **windspeed**, **dew**, **Severity**, and **solarradiation** appear to be among the most influential variables, as they have the highest number of splitting rules and comparatively low error rates.
- **windspeed** has the highest count, indicating it plays a significant role in prediction accuracy.
- Variables like windspeed and dew, which have high importance scores, suggest that these factors have a strong influence on the **Health_Risk_Score** (the dependent variable).

Model Performance Metrics

- **Average Squared Error (ASE)**: Training: **0.0158 ,**Validation: **0.0248**
- **Root Average Square Error (RASE)**: Training: **0.1253,** Validation: **0.1573**

Random Forest model has low error rates, suggesting good fit for this dataset.

Model 4 – Auto Neural Network

Why AutoNeural?

- AutoNeural simplifies the creation and optimization of neural networks, making it easier to configure and train models.
- It automatically selects the best configuration for the neural network, reducing manual tuning efforts.

Neural Network Architecture:

- **Input Layer:** Contains all independent variables (predictors) used in the model.
- **Hidden Layer:** Contains 3 hidden units, providing flexibility to capture complex relationships between input variables and the output. This choice strikes a balance between model complexity and overfitting.
- **Output Layer:** The dependent variable (health score risk) is the predicted output.

Key Benefits:

- Simplifies network design while maintaining flexibility.
- Efficiently captures non-linear patterns for accurate predictions.

Findings for Auto Neural Network

Performance Metrics:

- **Training ASE**: 0.4256 | **Validation ASE**: 0.4571 | **Test ASE**: 0.3901
- **Insight**: Low error rates indicate effective prediction of Health Risk Score.

Influential Variables

- Due to the nature of neural networks, specific variable importance isn't directly displayed; however, the model likely captured complex relationships among variables like **Heat Index**, **Humidity**, and **UV Index** that drive the Health Risk Score.

Complex Relationships Captured: Model captures multi-variable influences on health risk, though individual variable impacts aren't directly visible.

- **Hidden Variable Interactions**: Unlike decision trees, neural networks analyze combinations of variables, making them effective for capturing complex relationships affecting health risk scores.
- Specific variable impacts aren't directly visible, but the model's structure ensures all variables contribute to accurate predictions.

Model Comparision

Based on the Average Square Error (ASE) in the Fit Statistics table:

- Reg 5 has an ASE of 0.013009 for validation.
- HP Forest has an ASE of 0.021516 for validation.
- The Tree 2 Decision Tree has an ASE of 0.026706
- The Tree 1 Decision Tree has an ASE of 0.02849
- Auto Neural has an ASE of 0.457135

Fit Statistics

Selected Model	Predecessor Node	Model Node	Model Description	Train: Target Variable	Target Label	Selection Criterion: Valid: Average Squared Error
Y	Reg5	Reg5	Regressi...	Health R...		0.013009
	HPDMFo...	HPDMFo...	HP Forest	Health R...		0.021516
	Tree2	Tree2	Decision ...	Health R...		0.026706
	Tree	Tree	Decision ...	Health R...		0.02849
	AutoNeural	AutoNeural	AutoNeural	Health R...		0.457135

The Reg5 Regression Model has the lowest ASE (0.013009) on the validation data, making it the best model among the all based on average square error.

Business Recommendations

- **Implement Real-Time Public Health Alerts**

Use model predictions to issue alerts for high-risk air quality, helping vulnerable populations reduce exposure.

- **Guide Resource Allocation for Health Initiatives**

Prioritize deployment of resources (e.g., air purifiers, cooling stations) based on environmental factors influencing health risks.

- **Develop Targeted Preventative Health Campaigns**

Educate residents in high-risk areas on protective measures like mask-wearing and reduced outdoor activity during peak pollution.

- **Collaborate with Urban Planners for Long-Term Solutions**

Share insights with city planners to support zoning and green space initiatives that reduce pollution exposure.

- **Optimize Health Resource Planning**

Use risk predictions to help hospitals prepare for increased demand during pollution spikes.

Conclusion

- Analyzed the relationship between urban air quality and health impacts using machine learning models.
- **Heat Index, Humidity, and UV Index** are major contributors to Health Risk Score.
- **Stepwise Linear Regression** achieved the highest accuracy with minimal error, providing a clear and interpretable solution.
- Highlighted the need for monitoring key environmental factors to mitigate health risks, supporting informed decision-making in urban planning and healthcare.
- This model can guide policymakers and urban planners to develop targeted interventions for high-risk environmental conditions.
- This project demonstrates how machine learning and data analytics can provide actionable insights, underscoring the importance of environmental monitoring for public health.

References

Data Sources

- U.S. Environmental Protection Agency. **Air Quality Data**. epa.gov
- Centers for Disease Control and Prevention. **Environmental Health Tracking**. cdc.gov

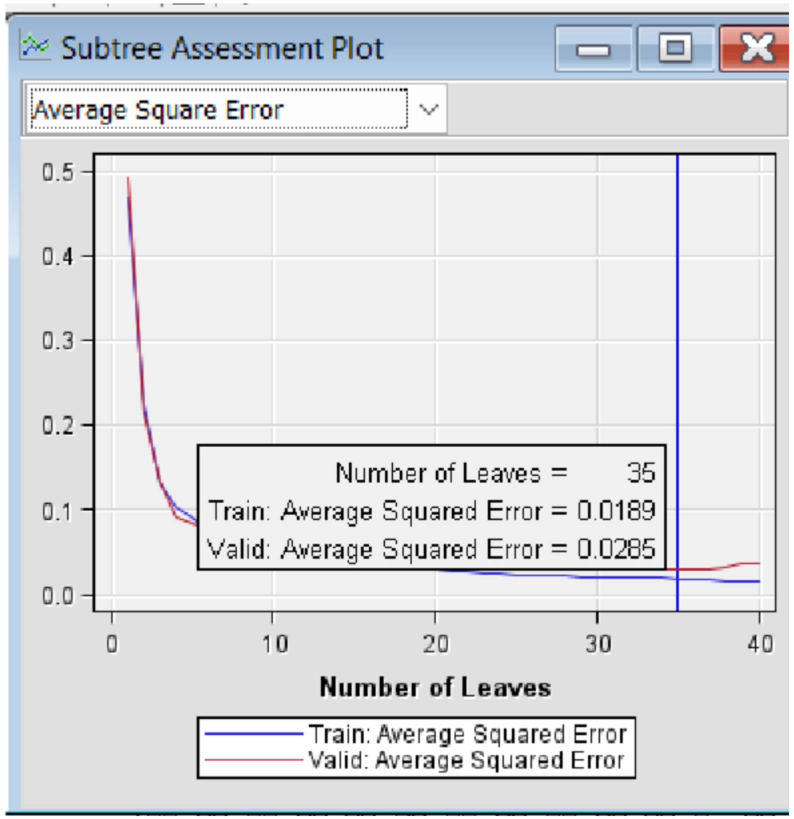
Machine Learning Techniques

- Hastie, T., Tibshirani, R., & Friedman, J. **The Elements of Statistical Learning**. Springer, 2009.
- Breiman, L. **Random Forests**. Machine Learning, 2001.

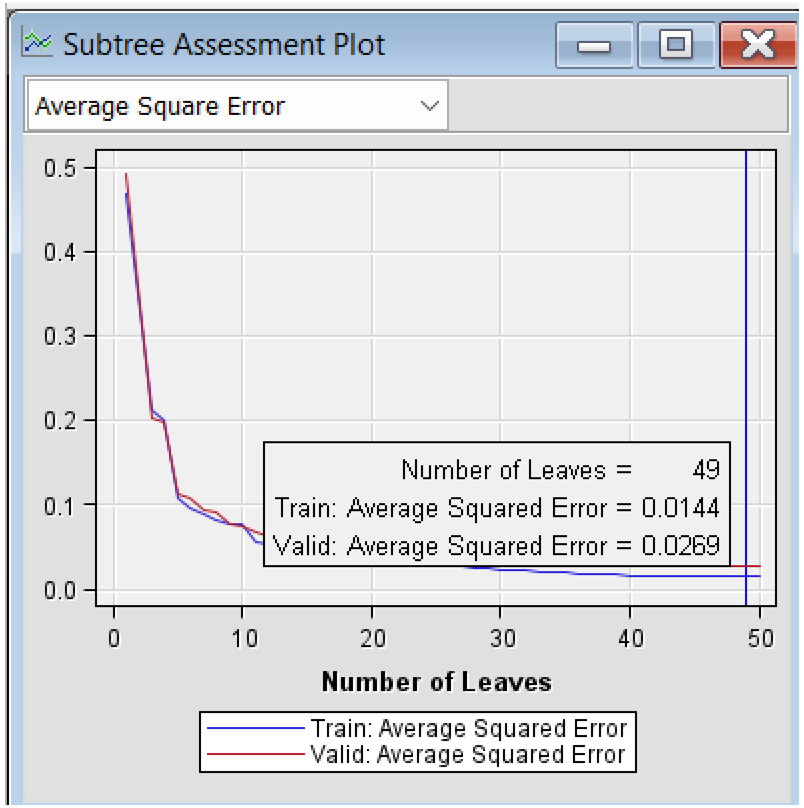
Environmental Health Studies

- Brook, R.D., et al. **Air Pollution and Cardiovascular Disease**. Circulation, 2010.
- Hoek, G., et al. **Long-term Air Pollution and Mortality**. Environmental Health, 2013.

IMPORTANT OUTPUT SCREENSHOTS

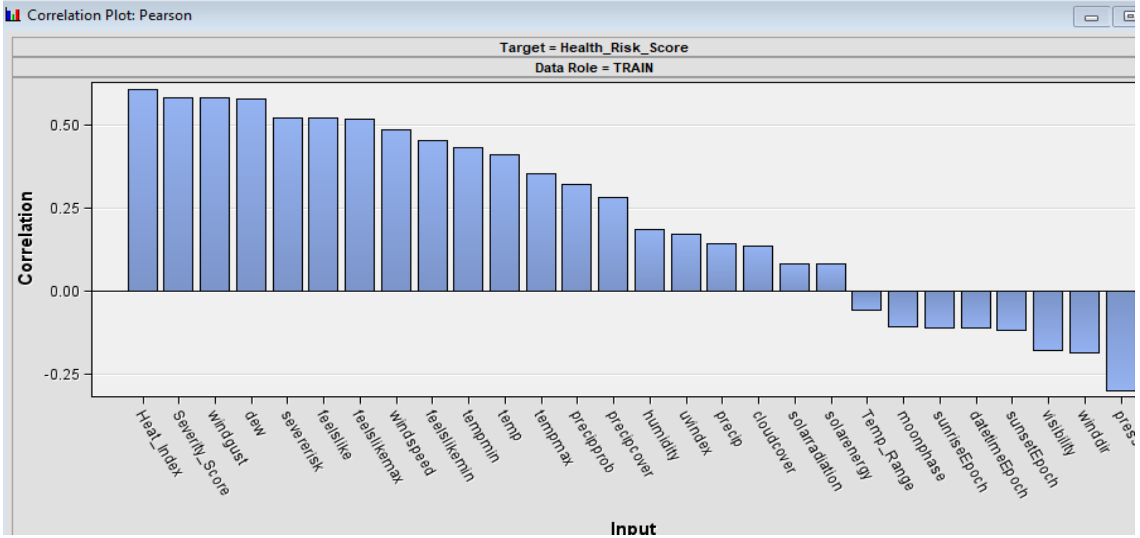


Decision tree 1



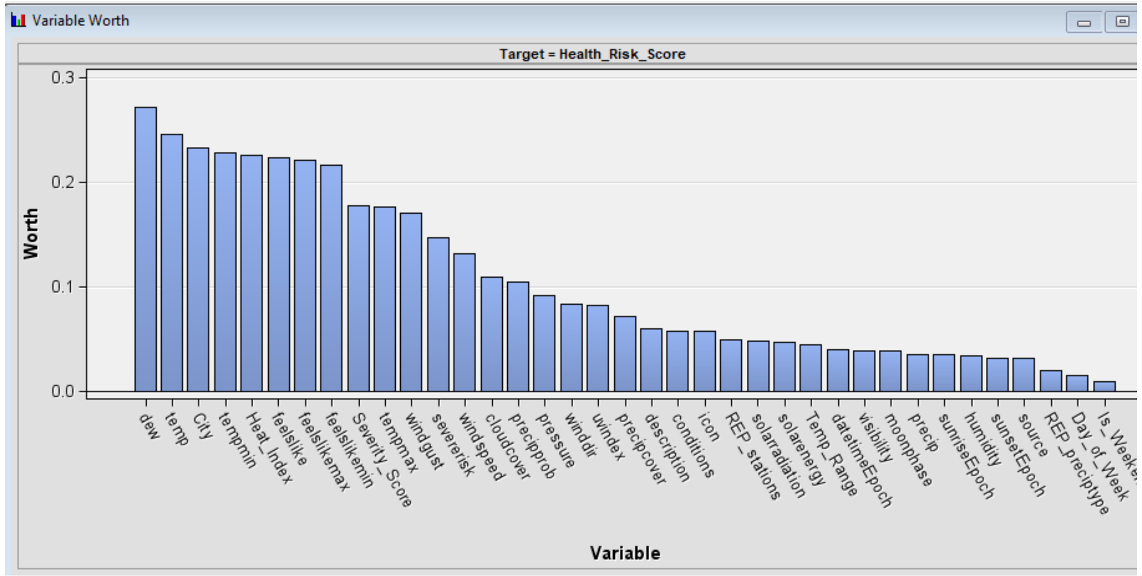
Decision tree 2

PLOTS

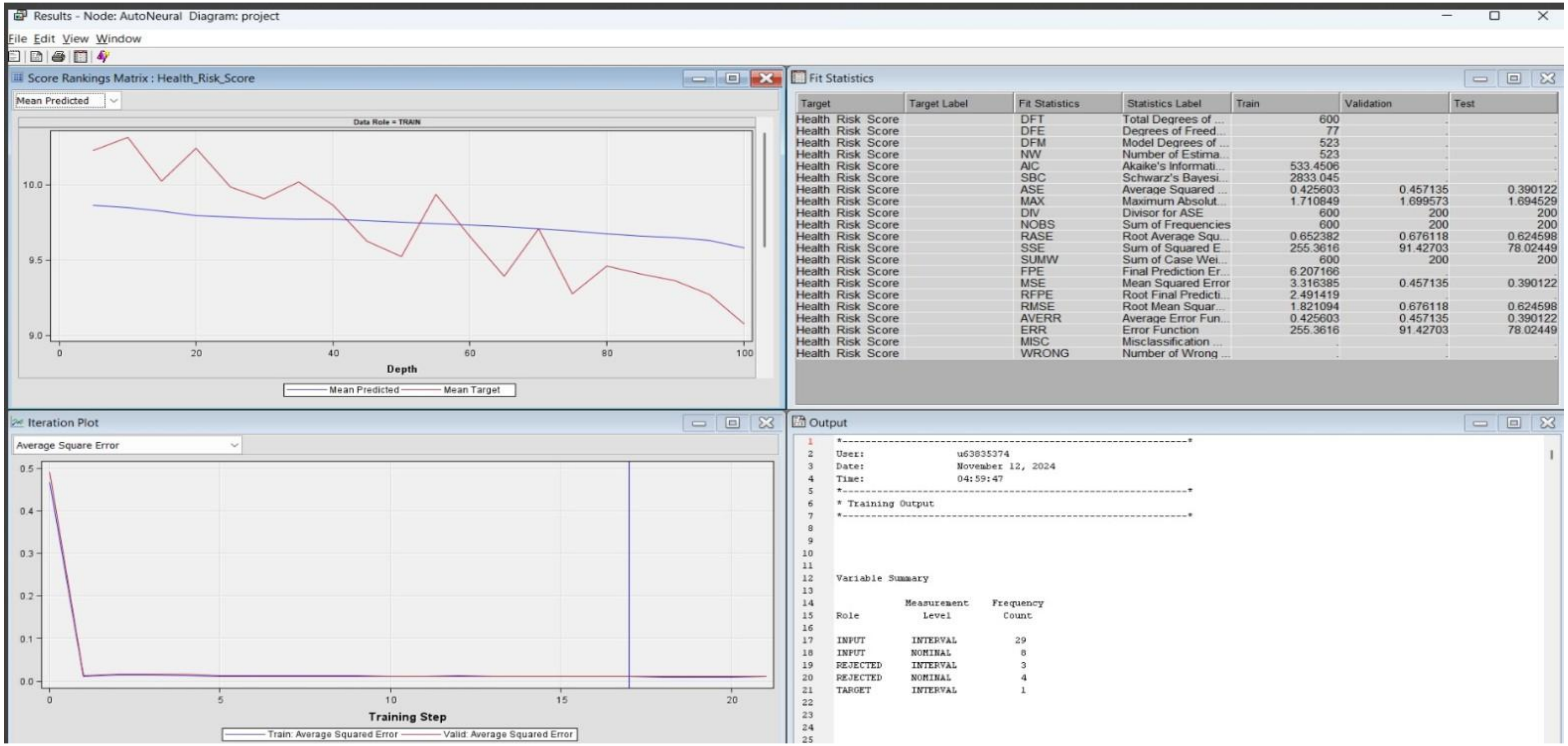


Correlation Plot – Correlation with Target Variable

Two variables are considered correlated if they change in the same direction. For example, the **heat index**, which represents the heat on a particular day, is strongly positively correlated with health risk, which makes sense given the impact of temperature on health. In contrast, **pressure** is negatively correlated with health risk, indicating that as pressure increases, health risk tends to decrease.



We also have a plot called **Variable Worth** in SAS Enterprise Miner, which evaluates the importance of each variable in the model. It shows how significant each variable is in predicting the target variable.



Auto Neural Network

The selected model is the model trained in the last step (Step 13). It consists of the following effects:

Intercept City Heat_Index LG10_precipcover LG10_solarenergy LG10_uvindex LG10_visibility Severity_Score dew feelslikemin humidity pressure winddir windgust

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	21	272.685091	12.985004	982.62	<.0001
Error	578	7.638098	0.013215		
Corrected Total	599	280.323189			

Model Fit Statistics

R-Square	0.9728	Adj R-Sq	0.9718
AIC	-2574.2687	BIC	-2571.9226
SBC	-2477.5362	C(p)	39.3157

Type 3 Analysis of Effects

Effect	DF	Sum of Squares	F Value	Pr > F
City	9	0.7143	6.01	<.0001
Heat_Index	1	31.4239	2377.95	<.0001
LG10_precipcover	1	0.1561	11.81	0.0006
LG10_solarenergy	1	0.2801	21.20	<.0001
LG10_uvindex	1	0.7387	55.90	<.0001
LG10_visibility	1	0.1539	11.65	0.0007
Severity_Score	1	0.6313	47.77	<.0001
dew	1	0.4102	31.04	<.0001
feelslikemin	1	0.2349	17.77	<.0001
humidity	1	4.1810	316.39	<.0001
pressure	1	0.1202	9.10	0.0027
winddir	1	0.4368	33.05	<.0001
windgust	1	0.2811	21.28	<.0001

Linear Regression - Stepwise

Model Fit Statistics

R-Square	0.7986	Adj R-Sq	0.7959
AIC	-1400.1945	BIC	-1397.9209
SBC	-1360.6222	C(p)	9.0000

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	9.7151	0.0126	770.02	<.0001
PC_1	1	0.1349	0.00461	29.24	<.0001
PC_3	1	-0.1136	0.00635	-17.90	<.0001
PC_4	1	0.1636	0.00856	19.11	<.0001
PC_5	1	0.2225	0.00950	23.41	<.0001
PC_6	1	0.1335	0.0117	11.44	<.0001
PC_7	1	0.000365	0.0127	0.03	0.9771
PC_8	1	0.1403	0.0137	10.23	<.0001
PC_9	1	0.0680	0.0154	4.42	<.0001

Principal Component Analysis Regression

Variable Distribution

Variables Summary Statistics

Class Variable Summary Statistics
(maximum 500 observations printed)

Data Role=TRAIN

Data Role	Variable Name	Role	Number of Levels	Missing	Mode	Mode Percentage	Mode2	Mode2 Percentage
TRAIN	City	INPUT	10	0	Chicago	13.10	New York City	11.30
TRAIN	Day_of_Week	INPUT	7	0	Saturday	20.50	Monday	13.90
TRAIN	Is Weekend	INPUT	2	0	False	66.80	True	33.20
TRAIN	conditions	INPUT	4	0	Clear	56.90	Partially cloudy	36.30
TRAIN	description	INPUT	12	0	Clear conditions throughout the	55.40	Partly cloudy throughout the day	28.90
TRAIN	icon	INPUT	4	0	clear-day	56.90	partly-cloudy-day	36.30
TRAIN	preciptype	INPUT	2	622		62.20	['rain']	37.00
TRAIN	source	INPUT	2	0	fcst	93.30	comb	6.70
TRAIN	stations	INPUT	11	933		93.30	['KORD', 'KMDW', 'F1983', 'KPWK'	1.20

Interval Variable Summary Statistics
(maximum 500 observations printed)

Data Role=TRAIN

Variable	Role	Mean	Standard Deviation	Non Missing	Missing	Minimum	Median	Maximum	Skewness	Kurtosis
Heat_Index	INPUT	80.19561	6.053805	1000	0	65.51168	78.55225	96.68416	0.367248	-0.40708
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cloudcover	INPUT	24.16015	22.43877	1000	0	-4.39913	17.3	101.5813	1.371373	1.394269
datetimeEpoch	INPUT	1.7263E9	374583.4	1000	0	1.7256E9	1.7263E9	1.727E9	0.023845	-6.4719
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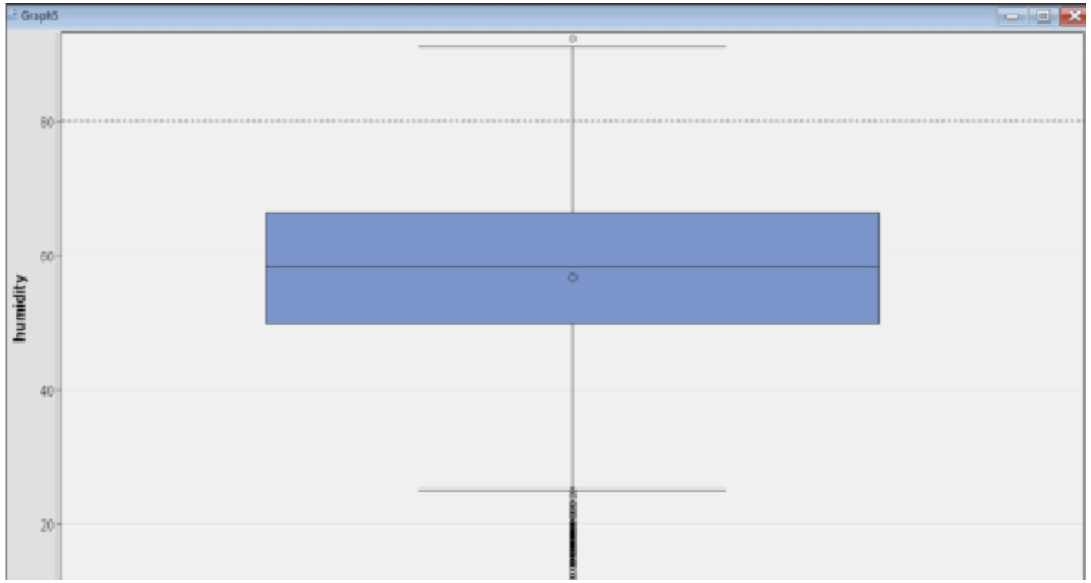
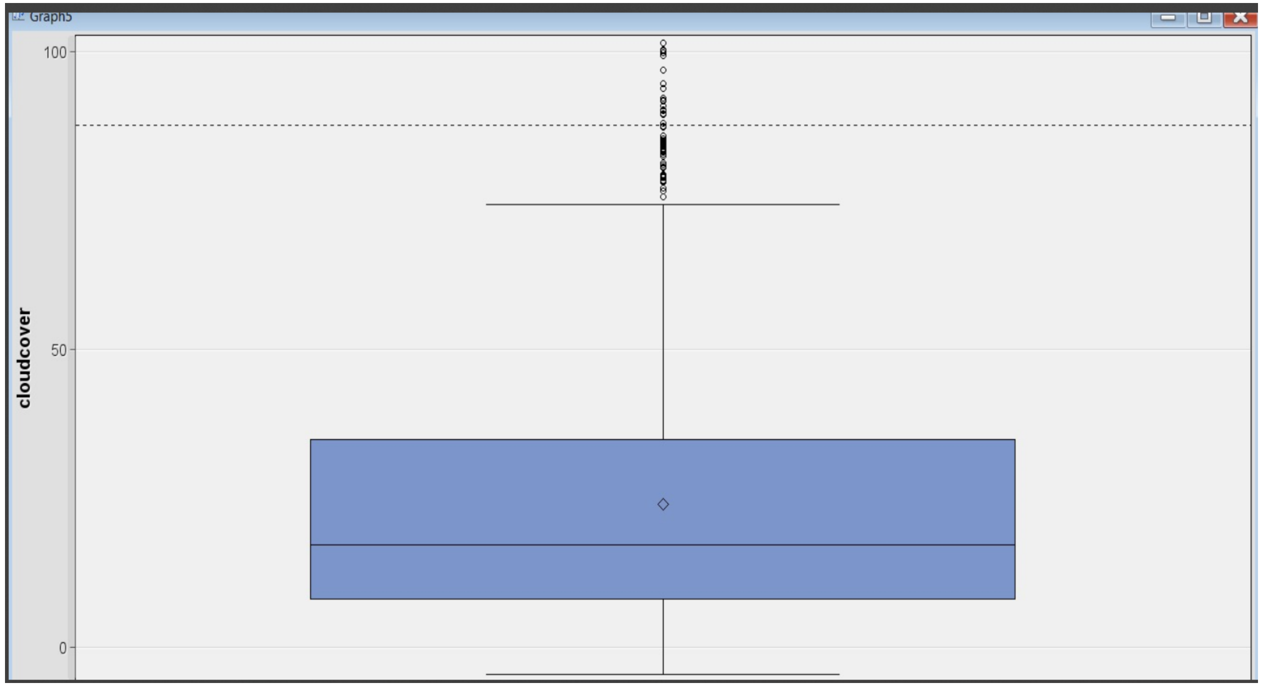
feelslikemax	INPUT	85.19538	9.496951	1000	0	62.20641	84.26815	105.0602	0.037509	-0.79648
feelslikemin	INPUT	68.54755	8.365809	1000	0	48.83404	67.84182	89.36985	0.08492	-0.69277
humidity	INPUT	56.78228	16.70867	1000	0	11.75213	58.40587	92.45929	-0.73347	0.549305
moonphase	INPUT	0.383811	0.147229	1000	0	0.123494	0.384836	0.649488	0.027052	-1.2763
precip	INPUT	0.032135	0.083461	1000	0	-0.02121	0.004	0.471666	3.459702	12.26739
precipcover	INPUT	3.033815	5.438894	1000	0	-1.93566	0.416568	25.58344	2.283406	4.990234
precipprob	INPUT	12.59944	17.8862	1000	0	-5.90159	5.448631	103.5391	2.484542	7.686922
pressure	INPUT	1014.03	5.56701	1000	0	1000.448	1012.516	1030.665	0.608769	0.018398
severerisk	INPUT	12.92369	8.838858	1000	0	7.507579	10.07979	61.72792	3.5772	14.09382
solarenergy	INPUT	21.02722	4.424434	1000	0	0.058881	22.1843	29.82179	-1.57395	3.823364
solarradiation	INPUT	243.5192	50.72456	1000	0	8.029656	257.3505	356.2738	-1.57201	3.815228
sunriseEpoch	INPUT	1.7263E9	375345.3	1000	0	1.7257E9	1.7263E9	1.727E9	0.022783	2.388576
sunsetEpoch	INPUT	1.7264E9	375301.2	1000	0	1.7257E9	1.7264E9	1.727E9	0.026347	-6.44549
temp	INPUT	76.11597	8.72207	1000	0	55.54841	75.2015	99.85168	0.348593	-0.52415
tempmax	INPUT	85.10696	9.524231	1000	0	62.03543	84.30467	107.7974	0.203739	-0.39198
tempmin	INPUT	68.64164	8.474102	1000	0	49.10822	67.69683	91.63555	0.153686	-0.57364
uvindex	INPUT	7.645897	1.566212	1000	0	-0.17961	8	10.16319	-1.78712	5.100451
visibility	INPUT	13.65487	2.111118	1000	0	8.24918	14.88931	15.71355	-1.04985	-0.6664
winddir	INPUT	170.1747	85.74123	1000	0	12.54583	161.3771	349.8395	0.103121	-1.10116
windgust	INPUT	15.22971	5.350923	1000	0	3.495792	14.91685	33.51684	0.325805	0.152767
windspeed	INPUT	9.87112	2.753853	1000	0	4.885928	9.58748	19.02312	1.023496	1.643456
Health_Risk_Score	TARGET	9.729103	0.679728	1000	0	8.492431	9.545693	11.48572	0.573568	-0.72551



Box Plot for Outlier Detection



Question?

Thank you