

WORLD TUBERCULOSIS 2023

Correlation and prediction of Tuberculosis incidences and severity level according to health, socio-economic and environmental factors



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WHO TUBERCULOSIS REPORT 2024

Tuberculosis (TB) = contagious lung infection caused by

Mycobacterium tuberculosis (MTB) bacteria.

TB was the world's leading infectious disease killer in 2023.
Worldwide 1.25 million people died due to TB in 2023.

Worldwide 10.8 million people fell ill with TB in 2023.

Development of incidence rates per country over time were reported.

Still no effective prevention (vaccine) available.

Bacillus Calmette-Guérin (BCG) vaccine statistics reported.

Only suboptimal treatment options available.
https://www.who.int/teams/global-tuberculosis-programme/data

DATA ENRICHMENT OF TUBERCULOSIS REPORT

Objective: Correlate TB incidences /severity level in 2023 with further disease-related information (treatment resistance & BCG vaccination rate), other health indicators (smoking rates), socioeconomic (population density, poverty index) and environmental (ALI POLIULION) circumstances.

Task: data acqusition and enrichment

- Data on treatment resistance & BCG vaccination rate downloaded from WHO
- Include air pollution data (average annual fine particulate matter <2.5 µm diameter in µg/m³) per country
 for 2025 obtained from IOAIR (https://www.iqair.com/us/world-mast-polluted-countries) or for 2019 from
 WHO (https://www.wbo.int/data/abs/data/themes/air-pollution/who-air-quality-database)
- Include multidimensional poverty index (MPI) data per country for 2025 obtained from UNDP (United Nations Development Programme) Human Development Report (HDR) (https://hdr.undp.org/content/2025-ajbobl-multidimensional-poverty-index-mpi)
- Include population density (https://database.earth/population/density/2023)
- Include smoking rates per country for 2022 (https://worldpopulationreview.com/country-rankings/smoking-rates-by-country)

DATA CLEANING AND WRANGLING



Preprocessing of data for modelling:

- all column names conclusive & lower case
- some columns dropped
- all values numerical
- · still many null values, replaced with NaN
- no duplicated values
- country iso2 and iso3 codes introduced

-> Extensive cleaning needed before table merging



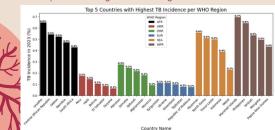
Top 5 countries per world region displayed according to:

- TB incidences
- treatment resistance
- BCG vaccination rate
- population density
 poverty index
- poverty indexsmoking rates
- air pollution
- TB severity

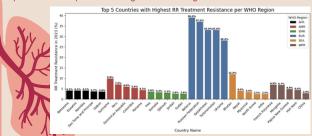
Three-letter code of the 6 WHO regions:

- AFR → African Region
- **AMR** → Region of the Americas
- EMR → Eastern Mediterranean Region
 EUR → European Region
- SEA → South-East Asia Region
- WPR → Western Pacific Region

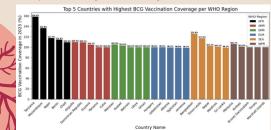
Top 5 countries per world region according to: TB incidences



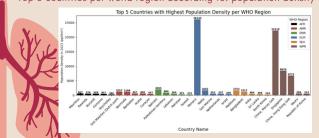
Top 5 countries per world region according to: treatment resistance



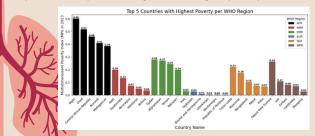
Top 5 countries per world region according to: BCG vaccination rate



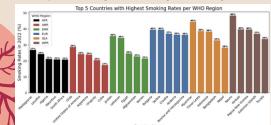
Top 5 countries per world region according to: population density



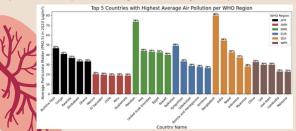
Top 5 countries per world region according to: poverty index



Top 5 countries per world region according to: smoking rates



Top 5 countries per world region according to: air pollution



TUBERCULOSIS INCIDENCES: SEVERITY LEVEL

Distribution of TB severity level in the 6 world regions (target)



FEATURE ENGINEERING AND SELECTION



Correlation of features with TB incidence:

3 features from TB

burden data set,7 enriched features ->

drop % pop in pov

DATA PREPARATION FOR PREDICTION MODELLING

total 214 countries: train & test split = 171 (80%) & 43 (20%) normalization: Min/Max scaling, tuning: hyperparameters balancing: impute NaN -> SMOTE, class weighting



	eIndex: 214 entries, 0 to 213 columns (total 9 columns): Column	Non-Null Coun
0	e_tbhiv_prct	214 non-null
1	cfr_pct	196 non-null
2	c_cdr	192 non-null
3	e_rr_pct_new	214 non-null
4	BCG_coverage	156 non-null
5	population_density	214 non-null
6	MPI_value	109 non-null
7	total_smokers_2022_percent	164 non-null
8	avg_air_pollution_PM2-5_in_2023	131 non-null

PREDICTION OF TB SEVERITY USING ML MODELS

Implement supervised ML models to predict TB severity levels

Ensemble prediction model testing:

- HistGradientBoostingClassifier
- RandomForestClassifier (DecTree + RandPatch)
 Model optimization:
 - hyperparameter tuning for HGBC model
 - impute missing NaN using KNN
 - target parameter balancing using SMOTE or Class Weight balancing on RFC model





EVALUATE PREDICTION MODEL'S PERFORMANCE

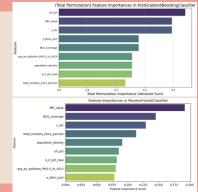
Evaluation according to prediction precision, recall, F1-score, accuracy



model	precision	recall	F1-score	accuracy
HistGradBoost	0.59	0.56	0.54	0.56
Random Forest	0.48	0.63	0.54	0.63
RFC + CW	0.47	0.65	0.54	0.65
RFC + SMOTE	0.58	0.49	0.47	0.49
RFC(CW)+SMOTE	0.38	0.40	0.38	0.40
HGBC_HT	0.47	0.65	0.54	0.65

EVALUATION

FEATURE IMPORTANCE



Aggregated Confusion Matrix of HGBC model: True vs. False Appregated Confusion Matrix of RFC model: True vs. False **EVALUATION** 19 True True CONFUSION **MATRICES** - 40 19 Predicted Label Predicted Label Apprepated Confusion Matrix of HGBC + HT model: True vs. False Aggregated Confusion Matrix of RFC + CW model: True vs. False 15 15 True Prue Label Dine False

Predicted Label

Predicted Label

PREDICTION OF TB SEVERITY USING ML MODELS

Implement unsupervised ML models to predict TB severity levels

Clustering prediction model testing:

- no train/test split, use whole data for clustering
- impute missing NaN using KNN, Min/Max norm.
- KMeans clustering (not useful)
 - Adjusted Rand Index (ARI): -0.0361 (similarity)
 Normalized Mutual Information (NMI): 0.0378 (dep.)
- create dendrogram to determine cluster no.
- Hierarchical clustering (not useful either)
 - Adjusted Rand Index (ARI): 0.1552 (similarity)
 - o Normalized Mutual Information (NMI): 0.1043 (dep.)

VISUALIZATIONS (TABLEAU)

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KEY FINDINGS AND INSIGHTS

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REAL WORLD APPLICATION AND IMPACT

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• XXXXX

CHALLENGES AND LEARNINGS

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FUTURE WORK AND IMPROVEMENTS



- try to fill in missing values for 2023
- try to find other data for enrichment with higher correlation to target
- include data of years before 2023

Improving supervised ML models:

• run time corrleated predictions

Improving unsupervised clustering models:

- Perform PCA before running unsupervised clustering models to reduce noise and redundant features.
- Experiment with different values of K for Kmeans (e.g., using the Elbow Method or Silhouette Score).
- Consider other clustering algorithms like DBSCAN.





THANK YOU!

Correlation and prediction of Tuberculosis incidences and severity level according to health, socio-economic and environmental factors (based on WHO Tuberculosis report 2024

