**ARTIFICIAL INTELLIGENCE OPTIMIZATION FOR COMPUTER SCIENTISTS — D682**

TASK 2: AI MODEL OPTIMIZATION

**B1. Optimization Techniques Implemented**

* **RandomizedSearchCV**: Explores a specified number of random hyperparameter combinations (n\_iter=200) across GBM’s parameters (n\_estimators, learning\_rate, max\_depth, subsample) using time-series cross-validation.
* **BayesianSearchCV**: Uses a probabilistic model to propose promising hyperparameters over 50 iterations, balancing exploration and exploitation more efficiently than random search.

**D1. Explanation of Optimization Techniques**

* **RandomizedSearchCV** was chosen for its simplicity and ability to cover wide hyperparameter spaces quickly, often finding near-optimal settings faster than exhaustive grid search.
* **BayesianSearchCV** leverages previous trial results to inform subsequent searches, improving convergence speed and finding better minima with fewer evaluations, essential when computational resources are limited.

**B2. Regularization Methods Implemented**

* **Shrinkage (learning\_rate)**: Included lower learning rates (down to 0.001) to make incremental updates smaller, reducing the risk of overfitting.
* **Subsampling**: Configured subsample < 1.0 (0.6, 0.8) to train trees on random subsets of data, introducing diversity and acting as a bagging-style regularizer.

**D2. Explanation of Regularization Methods**

* **Shrinkage** controls the influence of each tree; by taking smaller steps, the model generalizes better to unseen data, aligning with principles outlined in the original gradient boosting machine paper.
* **Subsampling** increases variance reduction through random sampling of observations, akin to bagging, which helps the ensemble avoid overfitting to anomalies or noise in the training set.

**B3. Ensemble Learning Techniques Implemented**

* **StackingRegressor** (ensemble\_stack.py): Combines three base learners—optimized GBM, RandomForest, LinearRegression; using a LinearRegression meta-learner to learn how to best blend predictions.
* **VotingRegressor** (ensemble\_vote.py): Averages predictions from optimized GBM, HistGradientBoosting, and LinearRegression, offering a simple, robust ensemble baseline.

**D3. Explanation of Ensemble Learning Techniques**

* **Stacking** leverages the complementary strengths of diverse models and allows a meta-learner to correct systematic errors, often yielding superior accuracy at the cost of complexity.
* **Voting** provides model-agnostic robustness by averaging, which smooths individual model idiosyncrasies and improves stability with minimal parameter tuning.

**C1. Evaluation Metrics Selected**

* **Root-Mean-Squared Error (RMSE)**: Measures average magnitude of prediction errors and heavily penalizes large deviations; standard in regression tasks.
* **Mean Absolute Error (MAE)**: Represents average error in original units; easier to interpret and less sensitive to outliers.

**D4. Explanation of Evaluation Metrics**

* **RMSE** highlights substantial mispredictions by squaring errors before averaging, crucial for health-risk forecasting where large underestimates can be dangerous.
* **MAE** facilitates straightforward communication of typical error to stakeholders (e.g., “on average, predictions are ±0.10 health-risk units”), improving transparency.

**C2. Comparison of Performance Metrics**

* **Baseline GBM**: RMSE 0.196; MAE 0.153
* **Optimized GBM**: RMSE 0.195; MAE 0.152 (≈ 0.5% improvement)
* **Stacking Ensemble**: RMSE 0.120; MAE 0.096 (≈ 39% reduction in RMSE)
* **Voting Ensemble**: RMSE 0.131; MAE 0.106 (≈ 33% reduction in RMSE)

**D5. Summary of Performance Analysis and Business Impact**

The marginal gain from hyperparameter tuning alone indicates near-optimal baseline settings. In contrast, ensembling, particularly stacking, yields significant error reduction, translating to more accurate air-quality and health-risk predictions.  
**Business Impact**: A 39% lower RMSE can reduce false alarms and missed alerts, leading to better resource allocation in public-health responses and enhanced trust from stakeholders.