

Model Development Phase Template

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Team ID	SWTID1720090524
Project Title	Garment Worker Productivity Prediction
Maximum Marks	6 Marks

Model Selection Report

In the forthcoming Model Selection Report, various models will be outlined, detailing their descriptions, hyperparameters, and performance metrics, including Accuracy or F1 Score or Root mean Squared Error. This comprehensive report will provide insights into the chosen models and their effectiveness.

Model Selection Report:

Model	Description	Hyperparameters	Performance Metric (e.g., Accuracy, F1 Score, Root Mean Squared Error)
Linear Regression Model	Describes the relationship between a dependent variable and one or more independent variables.	---	Train Root Mean Squared Error: 0.16226529653729893 Test Root mean Squared Error: 0.16116562949494234
Lasso Regression Model	In lasso regression, the hyperparameter lambda (λ), also known as the L1 penalty, balances the tradeoff between bias and variance in the resulting coefficients.	---	Train Root Mean Squared Error: 0.16246420183571206 Test Root Mean Squared Error: 0.16121034106828316

Ridge Regression Model	A linear regression model whose coefficients are estimated not by ordinary least squares (OLS), but by an estimator, called ridge estimator, that, albeit biased, has lower variance than the OLS estimator.	---	<p>Train Root Mean Squared Error: 0.16226837609384914</p> <p>Test Root mean Squared Error: 0.16115218890295427</p>
Decision Tree Regressor Model	Decision trees build regression or classification models in the form of a tree structure. It breaks down a dataset into smaller and smaller subsets while at the same time an associated decision tree is incrementally developed.	---	<p>Train Root Mean Squared Error: 0.13187559206436333</p> <p>Test Root mean Squared Error: 0.12918875831022705</p>
Random forest Regressor Model	A Random forest regression model combines multiple decision trees to create a single model. Each tree in the forest builds from a different subset of the data and makes its own independent prediction. The final prediction for input is based on the average or weighted average of all the individual trees' predictions.	---	<p>Train Root Mean Squared Error: 0.13062916799216504</p> <p>Test Root mean Squared Error: 0.1272406384012021</p>
Gradient Boosting Regressor Model	Gradient boosting regression trees are based on the idea of an ensemble method derived from a decision tree. The decision	---	<p>Train Root Mean Squared Error: 0.1424427737607694</p> <p>Test Root mean Squared Error: 0.13953081336729123</p>

	tree uses a tree structure. Starting from tree root, branching according to the conditions and heading toward the leaves, the goal leaf is the prediction result.		
Extreme Gradient Boosting Model	Extreme Gradient Boosting (XGBoost) is a decision-tree based ensemble that uses a more regularized model formalization to control over-fitting.	---	<p>Train Root Mean Squared Error: 0.12323119231675213</p> <p>Test Root mean Squared Error: 0.12085573039635658</p>
Bagging Regressor Model	A Bagging regressor is an ensemble meta-estimator that fits base regressors each on random subsets of the original dataset and then aggregate their individual predictions (either by voting or by averaging) to form a final prediction.	---	<p>Train Root Mean Squared Error: 0.11512255799809959</p> <p>Test Root mean Squared Error: 0.11683354248554284</p>
Boosting Regressor Model	Gradient boosting regression trees are based on the idea of an ensemble method derived from a decision tree. The decision tree uses a tree structure. Starting from tree root, branching according to the conditions and heading toward the leaves, the goal leaf is the prediction result.	---	<p>Train Root Mean Squared Error: 0.11456846365002314</p> <p>Test Root mean Squared Error: 0.12712298242901834</p>