

## Model Optimization and Tuning Phase Template

Date	July 2024
Team ID	739871
Project Title	Smart Home Temperature prediction using Machine Learning
Maximum Marks	10 Marks

### Model Optimization and Tuning Phase

The Model Optimization and Tuning Phase involves refining neural network models for peak performance. It includes optimized model code, fine-tuning hyperparameters, comparing performance metrics, and justifying the final model selection for enhanced predictive accuracy and efficiency.

#### Hyperparameter Tuning Documentation (8 Marks):

Model	Tuned Hyperparameters
Random Forest	<pre>#importing RandomForestRegressor from sklearn.ensemble import RandomForestRegressor</pre> <p>The parameter grid (param_grid) for hyperparameter tuning specifies different values for the number of trees (n_estimators), splitting criterion (criterion), maximum depth of trees (max_depth), and maximum features considered for splitting (max_features). The tuning process aims to optimize the model for accurately predicting smart home temperatures.</p>

## Linear Regression

```
rf=RandomForestRegressor()
rf.fit(x_train_scaled,y_train)

pred = rf.predict(x_test_scaled)

array([[22.38404202, 16.12649, 21.18897318, ..., 20.0831759,
        17.35389084, 21.610564 ]])

from sklearn.metrics import r2_score
r2_score(y_test,pred)

0.9470461932092306
```

### #importing LinearRegression

from sklearn.linear\_model LinearRegression

The parameter grid (param\_grid) for hyperparameter tuning specifies different values for the number of trees (n\_estimators), splitting criterion (criterion), maximum depth of trees (max\_depth), and maximum features considered for splitting (max\_features). The tuning process aims to optimize the model for accurately predicting smart home temperatures.

```
from sklearn.linear_model import LinearRegression
lir = LinearRegression()
lir.fit(x_train_scaled,y_train)

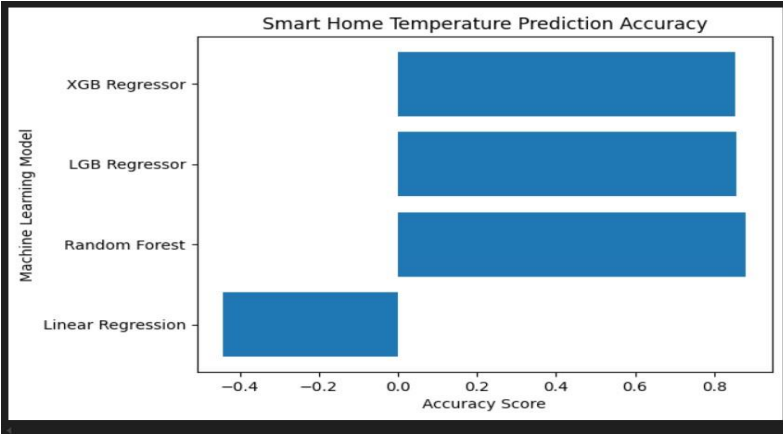
pred = lir.predict(x_test_scaled)

from sklearn.metrics import r2_score
r2_score(pred,y_test)

-0.4426495167688054
```

<p>LGB Regressor</p>	<p>The parameter grid (params) for hyperparameter tuning specifies different values for min_child_weight, gamma, colsample_bytree, and max_depth. The tuning process aims to optimize the model for accurately predicting smart home temperatures. GridSearchCV is employed with 5-fold crossvalidation (cv=5), refitting the best model (refit=True), and evaluating model performance based on accuracy (scoring="accuracy").</p> <pre> lgb = lgb.LGBMRegressor() ✓ 0.0s  lgb.fit(x_train,y_train) ✓ 0.4s  [LightGBM] [Info] Auto choosing row wise multi threading, the overhead of testing was 0.001325 seconds. You can set 'force_row_wise=True' to remove the overhead. And if memory is not enough, you can set 'force_col_wise=True'. [LightGBM] [Info] Total Bins 1539 [LightGBM] [Info] Number of data points in the train set: 2895, number of used features: 7 [LightGBM] [Info] Start training from score 18.884740  + LGBMRegressor ⓘ LGBMRegressor()  pred=lgb.predict(x_test) ✓ 0.0s  r2_score(y_test,pred) ✓ 0.0s 0.8569554882911747 </pre>
<p>XGB Regressor</p>	<p>The parameter grid (param_grid) for hyperparameter tuning specifies different values for the number of trees (n_estimators), splitting criterion (criterion), maximum depth of trees (max_depth), and maximum features considered for splitting (max_features). The tuning process aims to optimize the model for accurately predicting smart home temperatures.</p> <pre> xg=xgb.XGBRegressor() ✓ 0.0s  xg.fit(x_train,y_train) ✓ 3.1s  + XGBRegressor ⓘ XGBRegressor(base_score=None, booster=None, callbacks=None,              colsample_bylevel=None, colsample_bynode=None,              colsample_bytree=None, device=None, early_stopping_rounds=None,              enable_categorical=False, eval_metric=None, feature_types=None,              gamma=None, grow_policy=None, importance_type=None,              interaction_constraints=None, learning_rate=None, max_bin=None,              max_cat_threshold=None, max_cat_to_onehot=None,              max_delta_step=None, max_depth=None, max_leaves=None,              min_child_weight=None, missing=None, monotone_constraints=None,              multi_strategy=None, n_estimators=None, n_jobs=None,              num_parallel_tree=None, Random_state=None, ...)  pred=xg.predict(x_test) ✓ 0.0s  + Code + Markdown  r2_score(y_test,pred) ✓ 0.0s 0.8547022627762138 </pre>

## Final Model Selection Justification (2 Marks):

Final Model	Reasoning										
Random Forest	<p>Random Forest model is chosen for its robustness in handling complex datasets and its ability to mitigate overfitting while providing high predictive accuracy.</p> <div data-bbox="540 716 1318 1146">  <table border="1"> <caption>Smart Home Temperature Prediction Accuracy</caption> <thead> <tr> <th>Machine Learning Model</th> <th>Accuracy Score</th> </tr> </thead> <tbody> <tr> <td>XGB Regressor</td> <td>0.85</td> </tr> <tr> <td>LGB Regressor</td> <td>0.85</td> </tr> <tr> <td>Random Forest</td> <td>0.88</td> </tr> <tr> <td>Linear Regression</td> <td>-0.35</td> </tr> </tbody> </table> </div> <p>Above all the models Random Forest model have the highest accuracy among all the models.</p>	Machine Learning Model	Accuracy Score	XGB Regressor	0.85	LGB Regressor	0.85	Random Forest	0.88	Linear Regression	-0.35
Machine Learning Model	Accuracy Score										
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