

Model Optimization and Tuning Phase

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Skillwallet ID	SWUID20250194750
Project Title	Anemia Sense: Leveraging Machine Learning For Precise Anemia
Maximum Marks	10 Marks

Model Optimization and Tuning Phase

The Model Optimization and Tuning Phase involves refining machine learning 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(6Marks):

In this project, multiple classification algorithms were evaluated on a balanced version of the anemia dataset. While no explicit hyperparameter tuning (such as GridSearchCV or RandomizedSearchCV) was performed, the models were initialized with default or practical parameters known to work well in general cases. This allowed for rapid testing and comparison across models. Default settings yielded high accuracy for most classifiers, especially ensemble methods.

The table below outlines the key hyperparameters that would typically be tuned in each model, along with the values used in this project:

Model	Tuned Hyperparameters	Optimal Values
Logistic Regression	max_iter	1000
Decision Tree Classifier	criterion, max_depth, min_samples_split	Default
Random Forest Classifier	n_estimators, max_depth, max_features	Default

Gaussian Naive Bayes	None (no hyperparameters to tune in standard version)	Default
Support Vector Classifier	kernel, C, gamma	Default
Gradient Boost Classifier	n_estimators, learning_rate, max_depth	Default

Performance Metrics Comparison Report (2 Marks):

Model	Optimized Metric
Linear Regression	<pre> precision recall f1-score support 0 1.00 0.98 0.99 113 1 0.99 1.00 0.99 135 accuracy 0.99 macro avg 0.99 weighted avg 0.99</pre> <pre> con_lr = confusion_matrix(y_test, y_pred) print(con_lr) [[111 2] [0 135]]</pre>
Decision Tree	<pre> print('Accuracy Score: ',acc_dt) print(c_dt) Accuracy Score: 1.0 precision recall f1-score support 0 1.00 1.00 1.00 113 1 1.00 1.00 1.00 135 accuracy 1.00 macro avg 1.00 weighted avg 1.00</pre> <pre> con_lr = confusion_matrix(y_test, y_pred) print(con_lr) [[113 0] [0 135]]</pre>

Random Forest

```
print(c_rf)

              precision    recall  f1-score   support

     0       1.00      1.00      1.00     113
     1       1.00      1.00      1.00     135

 accuracy          1.00
 macro avg          1.00
weighted avg          1.00

con_lr = confusion_matrix(y_test, y_pred)
print(con_lr)

[[113   0]
 [   0 135]]
```

Gradient Boosting

```
c_gbc = classification_report(y_test,y_pred)
# print('Accuracy Score: ',acc_gbc)
print(c_gbc)

              precision    recall  f1-score   support

     0       1.00      1.00      1.00     113
     1       1.00      1.00      1.00     135

 accuracy          1.00
 macro avg          1.00
weighted avg          1.00

con_lr = confusion_matrix(y_test, y_pred)
print(con_lr)

[[113   0]
 [   0 135]]
```

Gaussian Naïve Bayes

```
print(c_nb)

              precision    recall  f1-score   support

     0       0.99      0.96      0.98     113
     1       0.97      0.99      0.98     135

 accuracy          0.98
 macro avg          0.98
weighted avg          0.98

con_lr = confusion_matrix(y_test, y_pred)
print(con_lr)

[[109   4]
 [   1 134]]
```

Support Vector Machine

```
print(c_svc)

              precision    recall  f1-score   support

     0       0.99      0.88      0.93     113
     1       0.91      0.99      0.95     135

 accuracy          0.95
 macro avg          0.93
weighted avg          0.94

con_lr = confusion_matrix(y_test, y_pred)
print(con_lr)

[[ 99  14]
 [   1 134]]
```

Final Model Selection Justification (2 Marks):

Final Model	Reasoning
Gradient Boosting	The Gradient Boosting model was selected for its superior performance, exhibiting high accuracy during hyperparameter tuning. Its ability to handle complex relationships, minimize overfitting, and optimize predictive accuracy aligns with project objectives, justifying its selection as the final model.