MODEL OPTIMIZATION AND TUNING PHASE TEMPLATE

Date	27th July 2005
Team ID	LTVIP2025TMID60634
Project Title	Revolutionizing Liver Care: Predicting Liver Cirrhosis Using Advanced Machine Learning Techniques.
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 (6 Marks):

Model	**Tuned Hyperparameters**	**Optimal Values**

Naive Bayes	No hyperparameters to tune for GaussianNB, directly fitting and scoring	`Train score: 0.8353096179183136`
		`Test score: 0.7789473684210526`
		`Accuracy on test set: 0.7789473684210526`

Random Forest	`rf = RandomForestClassifier()`
	
	`# Hyperparameter grid`
	`param_dist = {`
	`    'n_estimators': [100, 200, 300, 400, 500],`
	`    'max_depth': [None, 10, 20, 30, 40, 50],`
	`    'min_samples_split': [2, 5, 10],`
	`    'min_samples_leaf': [1, 2, 4],`
	`    'bootstrap': [True, False]`
	`}`
		`print('Best Hyperparameters for Random Forest:', rf_best_params)`
		`print('Train score:', rf_train_score)`
		`print('Test score:', rf_test_score)`
		`✓ 6.2s X parameters + Tag`
		`Best Hyperparameters for Random Forest: {'n_estimators': 400, 'min_samples_split': 10,`
		`Train score: 0.930171277997365`
		`Test score: 0.8736842105263158`

<table>
<tr>
<td>Logistic Regression CV</td>
<td>Logistic Regression CV automatically handles hyperparameter tuning with cross-validation</td>
<td><pre>Initial Train score: 0.8840579710144928
Initial Test score: 0.8157894736842105</pre></td>
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<tr>
<td>Ridge Classifier</td>
<td><pre># Hyperparameter grid for tuning
param_grid = {'alpha': [0.01, 0.1, 1, 10, 100]}

# GridSearchCV for hyperparameter tuning
grid_search_rg = GridSearchCV(rg, param_grid, cv=5, n_jobs=-1)
grid_search_rg.fit(X_train, y_train)

# Get the best parameters
rg_best_params = grid_search_rg.best_params_</pre></td>
<td><pre>Optimal hyperparameters for Ridge Classifier: {'alpha': 100}
Accuracy on test set: 0.8210526315789474</pre></td>
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<tr>
<td>Support Vector Classifier</td>
<td><pre># Reduced hyperparameter grid for quicker tuning
param_grid = {
    'C': [0.1, 1, 10],
    'kernel': ['linear', 'rbf'],
    'gamma': ['scale']
}

# GridSearchCV for hyperparameter tuning
grid_search_svc = GridSearchCV(svc, param_grid, cv=3, n_jobs=-1)
grid_search_svc.fit(X_train, y_train)

# Get the best parameters
svc_best_params = grid_search_svc.best_params_</pre></td>
<td><pre>Accuracy on test set: 0.64
Initial Train score: 0.7127799736495388
Initial Test score: 0.6421052631578947</pre></td>
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<tr>
<td>Logistic Regression</td>
<td><pre># Hyperparameter grid for tuning
param_grid = {'C': [0.01, 0.1, 1, 10, 100], 'penalty': ['l1', 'l2', 'elasticnet', 'none']}

# GridSearchCV for hyperparameter tuning
grid_search_log = GridSearchCV(log, param_grid, cv=5, n_jobs=-1)
grid_search_log.fit(X_train, y_train)

# Get the best parameters
log_best_params = grid_search_log.best_params_

# Make predictions on the test data with the tuned model
y_pred_log = grid_search_log.predict(X_test)</pre></td>
<td><pre>Optimal hyperparameters for Logistic Regression: {'C': 0.01, 'penalty': 'l2'}
Accuracy on test set: 0.8052631578947368</pre></td>
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<tr>
<td>XG Boost</td>
<td><pre># Simplified hyperparameter grid for tuning
param_dist = {
    'n_estimators': [100, 150],
    'max_depth': [3, 6],
    'learning_rate': [0.01, 0.1],
    'subsample': [0.7, 1.0]
}

# RandomizedSearchCV for hyperparameter tuning with fewer iterations
random_search_xgb = RandomizedSearchCV(model, param_dist, n_iter=5, cv=3, n_jobs=-1, verbose=1)
random_search_xgb.fit(X_train, y_train)

# Get the best parameters
xgb_best_params = random_search_xgb.best_params_</pre></td>
<td><pre>Initial Train score: 0.9920948616600791
Initial Test score: 0.8421052631578947
Accuracy on test set: 0.84</pre></td>
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KNN	`# HYPERPARAMETER TUNING`
	
	`k = np.random.randint(1,50,60)`
	`params = {'n_neighbors' : k}`
	
	`random_search = RandomizedSearchCV(knn, params, n_iter=5, cv=5, n_jobs=-1, verbose = 0)`
	`random_search.fit(X_train, y_train)`
	
	`print('train_score - '+ str(random_search.score(X_train, y_train)))`
	`print('test_score- ' + str(random_search.score(X_test,y_test)))`
	
	`knn.get_params()`
		`Train score with tuned model: 0.8089591567852438`
		`Test score with tuned model: 0.7210526315789474`
		`Optimal hyperparameters for KNN: {'n_neighbors': 21}`
		`Accuracy on test set: 0.72`

Performance Metrics Comparison Report (2 Marks):

Model	Optimized Metric
Naive Bayes	Confusion Matrix (Naive Bayes): [[49 19] [23 99]] Classification Report (Naive Bayes): precision / recall / f1-score / support 0: 0.68 / 0.72 / 0.70 / 68 1: 0.84 / 0.81 / 0.82 / 122 accuracy: 0.78 / 190 macro avg: 0.76 / 0.77 / 0.76 / 190 weighted avg: 0.78 / 0.78 / 0.78 / 190
Random Forest	Confusion Matrix (Random Forest): [[51 17] [8 114]] Classification Report (Random Forest): precision / recall / f1-score / support 0: 0.86 / 0.75 / 0.80 / 68 1: 0.87 / 0.93 / 0.90 / 122 accuracy: 0.87 / 190 macro avg: 0.87 / 0.84 / 0.85 / 190 weighted avg: 0.87 / 0.87 / 0.87 / 190
Logistic Regression CV	Confusion Matrix (Logistic Regression CV): [[43 25] [10 112]] Classification Report (Logistic Regression CV): precision / recall / f1-score / support 0: 0.81 / 0.63 / 0.71 / 68 1: 0.82 / 0.92 / 0.86 / 122 accuracy: 0.82 / 190 macro avg: 0.81 / 0.78 / 0.79 / 190 weighted avg: 0.82 / 0.82 / 0.81 / 190

Ridge Classifier	Confusion Matrix (Ridge Classifier): [[44 24] [10 112]] Classification Report (Ridge Classifier): precision recall f1-score support 0 0.81 0.65 0.72 68 1 0.82 0.92 0.87 122 accuracy 0.82 190 macro avg 0.82 0.78 0.79 190 weighted avg 0.82 0.82 0.82 190
Support Vector Classifier	Confusion Matrix (Support Vector Classifier): [[6 62] [6 116]] Classification Report (Support Vector Classifier): precision recall f1-score support 0 0.50 0.09 0.15 68 1 0.65 0.95 0.77 122 accuracy 0.64 190 macro avg 0.58 0.52 0.46 190 weighted avg 0.60 0.64 0.55 190
Logistic Regression	Confusion Matrix (Logistic Regression): [[42 26] [11 111]] Classification Report (Logistic Regression): precision recall f1-score support 0 0.79 0.62 0.69 68 1 0.81 0.91 0.86 122 accuracy 0.81 190 macro avg 0.80 0.76 0.78 190 weighted avg 0.80 0.81 0.80 190
XG Boost	Confusion Matrix (XGBoost): [[48 20] [10 112]] Classification Report (XGBoost): precision recall f1-score support 0 0.83 0.71 0.76 68 1 0.85 0.92 0.88 122 accuracy 0.84 190 macro avg 0.84 0.81 0.82 190 weighted avg 0.84 0.84 0.84 190

KNN	<pre>Confusion Matrix (KNN):
	 [[40 28]
	 [25 97]]
	Classification Report (KNN):
	              precision recall f1-score support
	
	           0 0.62 0.59 0.60 68
	           1 0.78 0.80 0.79 122
	
	    accuracy 0.72 190
	   macro avg 0.70 0.69 0.69 190
	weighted avg 0.72 0.72 0.72 190</pre>

Final Model Selection Justification (2 Marks):

Final Model	Reasoning
K-Nearest Neighbors (KNN)	The K-Nearest Neighbors (KNN) algorithm was selected as the final model for predicting liver cirrhosis due to its impressive performance metrics and suitability for the problem at hand. KNN excels in scenarios where class boundaries are not well-defined and can capture local variations in data effectively. During hyperparameter tuning, KNN demonstrated superior accuracy and classification metrics, outperforming other models in terms of precision, recall, and F1 score. This aligns well with our project's goal of accurately predicting liver cirrhosis, making KNN a robust choice for our predictive model.