

Explainability of AIML Decisions

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Overview

This report highlights the implementation of explainability methods to interpret AI model predictions in the context of financial loss prediction from cybersecurity incidents. Techniques used include SHAP and LIME, which help improve transparency and trust in AI decisions.

Anomaly Detection

An Isolation Forest model was used to detect anomalies with 5% contamination.

Anomaly Detection Results

Normal : 2850

Anomaly : 150

Regression Model Comparison

Four models were compared based on MSE and R^2 . Linear Regression was chosen as the best model.

Linear Regression: MSE=0.98, R^2 =-0.004

Random Forest : MSE=1.06, R^2 =-0.085

Gradient Boosting: MSE=1.00, R^2 =-0.021

XGBoost : MSE=1.27, R^2 =-0.301

Best Model : Linear Regression

3. SHAP Explainability

SHAP was used to evaluate global and local feature impact on model output.

4. LIME Explainability

LIME was applied to explain individual predictions using local feature contributions.

Saved Artifacts

- `best_regressor_model.joblib` — trained model
- `isolation_forest_model.joblib` — anomaly detection model
- `label_encoders.pkl` — saved encoders for categorical features
- `scaler.pkl` — saved StandardScaler for reproducibility

6) SHAP & LIME Visualizations



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4 Anomaly Detection

from sklearn.ensemble import IsolationForest
iso_model = IsolationForest(contamination=0.05, random_state=42)
data['Anomaly'] = iso_model.fit_predict(data.drop('Financial Loss (in Million $)', axis=1))
data['Anomaly'] = data['Anomaly'].map({1: 'Normal', -1: 'Anomaly'})
print(data['Anomaly'].value_counts())

Anomaly
Normal    2850
Anomaly    150
Name: count, dtype: int64

5 Regression Model Comparison

[5] features = data.drop(columns=['Financial Loss (in Million $)', 'Anomaly'])
    target = data['Financial Loss (in Million $)']
    X_train, X_test, y_train, y_test = train_test_split(features, target, test_size=0.2, random_state=42)

def evaluate_model(name, model):
```

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```
return (name, model, mse, r2)

models = [
    ('Linear Regression', LinearRegression()),
    ('Random Forest', RandomForestRegressor(n_estimators=100, random_state=42)),
    ('Gradient Boosting', GradientBoostingRegressor(n_estimators=100, random_state=42)),
    ('XGBoost', XGBRegressor(n_estimators=100, random_state=42, verbosity=0))
]
results = [evaluate_model(n, m) for n, m in models]
results.sort(key=lambda x: x[2])
best_name, best_model, _, _ = results[0]
print(f"Best Model: {best_name}")
```

Linear Regression: MSE=0.98, R2=-0.004
Random Forest: MSE=1.06, R2=-0.085
Gradient Boosting: MSE=1.00, R2=-0.021
XGBoost: MSE=1.27, R2=-0.301
Best Model: Linear Regression

6 Explainability with SHAP

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```
[6] explainer = shap.Explainer(best_model, X_train)
shap_values = explainer(X_test)
shap.summary_plot(shap_values, X_test)
shap.plots.waterfall(shap_values[0])
```

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