**Here’s the final copy-paste ready summary with Results and Explanations (no "verdict" word used) for seamless use in your presentation or documentation:**

**Classification Metrics**

* **Accuracy – Measures overall correctness of the classifier (both missing and not missing cases) | Result: 1.0 | Formula: (True Positives + True Negatives) ÷ Total Predictions | The model correctly predicted all cases with no errors.**
* **Balanced Accuracy – Balances recall for both classes to adjust for class imbalance | Result: 1.0 | Formula: (Recall for Missing + Recall for Not Missing) ÷ 2 | The classifier performs equally well on both missing and present cases, even if the dataset is skewed.**
* **Precision – Of the cases predicted as missing, how many were actually missing | Result: 1.0 | Formula: True Positives ÷ (True Positives + False Positives) | All predicted missing values were truly missing, so no false positives occurred.**
* **Recall – Of the actual missing cases, how many were correctly detected | Result: 1.0 | Formula: True Positives ÷ (True Positives + False Negatives) | The model detected all missing values without missing any cases.**
* **F1 Score – Harmonic mean of precision and recall for balanced performance | Result: 1.0 | Formula: 2 × (Precision × Recall) ÷ (Precision + Recall) | Indicates perfect performance with no trade-off between precision and recall.**
* **Confusion Matrix Values – True Positives = 127, True Negatives = 425, False Positives = 0, False Negatives = 0 | No formula | The classifier made no mistakes in any category, confirming perfect performance.**

**Regression Metrics (PayUp Prediction)**

* **R² (R-Squared) – Measures how much of the PayUp variance is explained by the model | Result: 0.9998 | Formula: 1 – (Sum of Squared Errors ÷ Total Variance) | The model explains almost all the variability in PayUp values, meaning it fits the data extremely well.**
* **MAE (Mean Absolute Error) – Average magnitude of prediction errors | Result: 0.0167 | Formula: Sum of |Actual – Predicted| ÷ N | The model's average error is very small, indicating predictions are close to actual PayUp values.**
* **RMSE (Root Mean Squared Error) – Penalises large errors more than MAE | Result: 0.0262 | Formula: √(Sum of (Actual – Predicted)² ÷ N) | No large outliers were detected in the errors, as the RMSE remains low.**
* **MAPE (Mean Absolute Percentage Error) – Percentage-based error measurement | Result: 3 × 10¹² % (Invalid) | Formula: (Sum of |Actual – Predicted| ÷ |Actual|) × 100 ÷ N | MAPE is not valid because some PayUp values are zero, leading to division by zero and unrealistically large percentages. This is expected in datasets where some prices or payments are zero. MAE and RMSE are sufficient to confirm model quality.**
* **Residual Mean – Checks for average prediction bias | Result: 0.00005 | Formula: Sum of (Actual – Predicted) ÷ N | The average prediction error is practically zero, showing the model is not systematically overpredicting or underpredicting.**
* **Residual Standard Deviation – Measures spread of prediction errors | Result: 0.0262 | Formula: √(Sum of (Residual – Mean Residual)² ÷ N) | The error spread is low, indicating consistent and stable predictions without unexpected deviations.**

**Anomaly Detection Metrics**

* **Anomaly Score – Measures how unusual each record is | Average Result: 0.4498 | Formula: Negative of IsolationForest’s score\_samples | Most records are within normal behaviour, as the average anomaly score is well below the anomaly threshold.**
* **Anomaly Threshold (99th Percentile) – The cut-off for flagging a record as anomalous | Result: 0.6037 | Formula: 99th Percentile of Anomaly Scores | Only the most extreme 1% of cases are flagged, ensuring strict and controlled anomaly detection.**
* **Total Anomalies Detected – Number of records classified as anomalies | Result: 6 records | Formula: Count of records where Anomaly Score > Threshold | About 1% of the data was flagged as anomalous, consistent with the configured detection level.**
* **Anomaly Detection Rate – Proportion of data flagged as anomalies | Result: 1.09% | Formula: (Total Anomalies ÷ Total Records) × 100 | The rate aligns with expectations, slightly over 1% due to tied anomaly scores near the threshold.**
* **Anomaly Score Standard Deviation – Variability in anomaly scores | Result: 0.0492 | Formula: Standard deviation of anomaly scores | Scores are clustered closely together, showing the model’s detection is stable and not erratic.**
* **Maximum Anomaly Score – The most extreme anomaly in the dataset | Result: 0.6271 | Formula: Max of anomaly scores | No catastrophic anomalies were found; the most anomalous point is just slightly over the threshold, indicating mild outliers.**

**Summary Notes**

* **Classification performed perfectly with no errors in detecting missing vs present PayUp.**
* **Regression achieved near-zero errors, with MAE and RMSE confirming accuracy; MAPE is invalid due to actual PayUp values of zero, which is expected and acceptable in financial data.**
* **Anomaly Detection flagged ~1% of data points as anomalies as configured, with no extreme outliers or data quality concerns.**

**This is fully optimised for quick reading, stakeholder explanation, and direct copy-paste into slides or Word documents.**

**Would you like me to prepare a Q&A cheat sheet or a visual chart next?**