A Novel Scoring-based Agile Sprint Deliverability Prediction and Prioritization using Machine Learning

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ABSTRACT
Accurate sprint deliverability estimation is pivotal for effective agile software development, yet traditional heuristic methods often yield subjective and inconsistent results, undermining project velocity. This study presents a machine learning (ML)-based framework to predict sprint deliverability, leveraging natural language processing (NLP) and historical data from the PROMISE (5,328 instances) and COQUINA (1,201 requirements) datasets. The framework employs TF-IDF-weighted Word2Vec embeddings for feature extraction, enhanced by SMOTE to address class imbalance, and utilizes XGBoost, Random Forest, and Support Vector Machines within an ensemble classifier framework for pseudo-labeling to classify requirements and forecast deliverability. A novel deliverability score, calculated as 0.3, combines requirement length, XGBoost confidence, type weights, and cosine similarity to PROMISE centroids, validated with 91% stakeholder agreement at COQUINA Software Company. Empirical results demonstrate XGBoost outperforming baselines with an AUC of 0.9995, reducing planning errors by 12% and improving efficiency by 15% across five sprints, while PCA and ROC curves enhance interpretability. This framework, integrated with Agile tools like Jira, offers a scalable, data-driven solution, addressing gaps in real-time adaptability and generalizability, and advancing intelligent agile planning for high-impact software development.

General Terms
Prediction, Software Development, Efficiency, Planning, and Analysis

Keywords
Sprint Deliverability, Predictive Modeling, Agile Prioritization, Machine Learning, Requirement Analysis.

1. INTRODUCTION
Agile methodologies, including Scrum and Kanban, facilitate iterative software development through their emphasis on flexible planning and continuous stakeholder collaboration (Awan et al., 2023). A persistent challenge within Agile sprint planning, however, lies in accurately forecasting the successful completion of individual requirements within defined sprint boundaries—a critical metric referred to as sprint deliverability. Conventional estimation practices, heavily reliant on subjective judgment or simplistic heuristics, frequently lead to imprecise deliverability predictions. This often results in issues such as overcommitment, missed deadlines, or underutilization of team capacity, thereby undermining project velocity and eroding stakeholder trust (Venkatesha, 2024; Vaidyanathan et al., 2024).

Machine learning (ML) presents a compelling alternative for enhancing deliverability prediction by systematically leveraging historical sprint data and textual requirement analysis to generate more objective deliverability forecasts. While previous research has explored ML applications in requirement classification and risk assessment (Sherif et al., 2022; Muhammad et al., 2022), a notable gap persists in the development of a quantifiable, comprehensive deliverability score. Such a score would integrate textual feature analysis, model confidence, and historical performance metrics to provide actionable guidance for Agile prioritization. This limitation hinders Agile teams' ability to make truly data-driven decisions during sprint planning.

This study addresses this gap by developing a machine learning framework designed to predict sprint deliverability for software requirements, thereby supporting more effective prioritization in Agile development. The specific objectives guiding this research are to:

(i) Collect and preprocess the PROMISE dataset, publicly available from the PROMISE Repository, to capture general requirement characteristics, and the COQUINA dataset, a proprietary project dataset with deliverability metrics derived from historical data and enhanced through preprocessing, to support sprint planning analysis.

(ii) Engineer a comprehensive feature set to comprehensively quantify requirement attributes pertinent to deliverability, supporting subsequent predictive modeling.

(iii) Train and evaluate XGBoost, Random Forest, and Support Vector Machines as supervised learning algorithms to develop a predictive model for deliverability, and explore an ensemble approach to establish ground truth for unlabelled COQUINA data, enhancing prediction stability.

(iv) Develop a clear, interpretable deliverability scoring system complemented by insightful visualizations to empower stakeholders in their decision-making processes.

By synthetically combining requirement textual characteristics, predictive model confidence, and historical sprint outcomes into a novel deliverability framework, this research aims to overcome the inherent limitations of subjective manual estimations. This approach will enable more precise backlog prioritization, reduce project risks, and significantly enhance Agile teams' responsiveness to dynamic project demands.

2. LITERATURE REVIEW
The application of machine learning (ML) to Agile requirement management has gained traction for addressing challenges in classifying, prioritizing, and predicting the deliverability of software requirements in dynamic sprint environments. This review synthesizes technical advancements in ML-driven requirement classification, feature extraction, and sprint deliverability estimation, aligning with the aim to develop an

ML framework that classifies requirements and predicts sprint deliverability using PROMISE and COQUINA datasets, TF-IDF weighted Word2Vec, and ensemble classifiers (XGBoost, Random Forest, SVM).

Requirement Classification and Feature Extraction: ML techniques have been widely explored for classifying software requirements into functional and non-functional types, a critical step for Agile prioritization. Kurtanović and Maalej [6] employed supervised learning with Word2Vec and SVM classifiers to categorize requirements, achieving high accuracy on the PROMISE dataset (969 instances), though their approach struggled with semantic variability across domains. Similarly, Yang et al. [18] utilized XGBoost and logistic regression on preprocessed requirement texts, reporting a correlation (rho = 0.5927, p = 5.753e-06) for classification tasks. Their use of TF-IDF and chi-squared feature selection improved model performance but highlighted challenges in handling sparse datasets. In contrast, Navarro-Almanza et al. [8] applied deep learning for non-functional requirement (NFR) classification, leveraging neural networks to capture semantic nuances, though computational complexity limited scalability. Obike et al. [9] advanced this domain by proposing a feature engineering approach for Agile requirement management, utilizing semantic analysis with TF-IDF-weighted Word2Vec embeddings to enhance requirement classification accuracy. Their study demonstrated that integrating semantic similarity metrics improved the robustness of feature sets derived from Agile datasets, addressing variability issues noted in prior work, though it emphasized classification over deliverability prediction. These studies align with Objective 1 (collecting and preprocessing PROMISE and COQUINA datasets) and Objective 2 (extracting TF-IDF weighted Word2Vec embeddings), but they lack focus on sprint-specific deliverability, a gap this study addresses.

ML-Driven Prioritization and Deliverability Prediction: Prioritization in Agile contexts require quantifying requirement impact on sprint outcomes. Selvaraj and Choi [12] explored swarm intelligence algorithms for prioritizing user stories based on stakeholder feedback and complexity, but their approach did not incorporate deliverability scoring. Cando and Mendes [2] used SVM and Word2Vec to prioritize requirements, integrating historical project data to estimate effort, yet their models lacked real-time adaptability for sprint planning. Yahya et al. [17] proposed a hybrid deep learning model combining convolutional and recurrent neural networks, achieving robust prioritization by analyzing requirement text and historical sprint performance. However, their reliance on static datasets limited generalizability, a challenge addressed in this study through Objective 3 (training XGBoost, Random Forest, and SVM with ensemble pseudo-labeling on PROMISE and COQUINA data).

Sprint Deliverability and Scoring Systems: Estimating sprint deliverability remains underexplored. Venkatesha [16] highlighted the potential of ML to predict requirement impact on sprint goals, but their work focused on risk assessment rather than deliverability scoring. Orekha et al. [10] employed natural language understanding (NLU) to classify requirements and estimate effort, using features like requirement length and semantic similarity. Their models, however, did not integrate heuristic features (e.g., type weights) or provide a quantifiable deliverability score. The current study builds on these efforts by developing a weighted scoring function combining requirement length, model confidence, and semantic similarity to historical stories, validated at COQUINA Software Company with 91% expert agreement. This scoring system, supported by visualizations (e.g., feature importance, score distributions), enhances stakeholder decision-making in Agile environments.

Integration with Agile Tools: Practical adoption of ML frameworks requires seamless integration with tools like Jira or Azure DevOps. Dugharney and Kehinde [4] noted challenges in integrating ML models due to biased training data and poor interpretability. Franch [5] proposed data-driven requirement engineering (DDRE) using NLP for real-time feedback analysis, but their approach lacked sprint-specific scoring.

Research Gap and Limitations: While prior studies [13],[14] advanced requirement classification and dynamic documentation, they did not develop a unified framework for sprint deliverability prediction. Limitations in existing work include reliance on static datasets, limited generalizability across Agile contexts, and lack of interpretable scoring systems [3],[11]. This study mitigates these by using diverse datasets (PROMISE and COQUINA), ensemble pseudo-labeling for robustness, and a deliverability scoring module validated in real-world settings.

In summary, this review underscores the potential of ML to transform Agile requirement management. By addressing the gap in sprint deliverability prediction, this study's framework, leveraging TF-IDF weighted Word2Vec, ensemble classifiers, and a novel scoring system, offers a practical and scalable solution for Agile teams, as outlined in the objectives. The semantic analysis approach by Obike et al. [9] further supports this effort, providing a foundation for enhancing feature engineering that this study extends to deliverability prediction.

3. RESEARCH METHODOLOGY

This study develops a predictive framework for assessing the deliverability of requirements in an agile software development environment, utilizing data from the PROMISE Expanded Dataset and COQUINA Software Company Limited, Uyo. The methodology encompasses data collection, preprocessing, feature engineering, model development, deliverability scoring, and evaluation, designed to align with the objective of accurately predicting sprint deliverability. Ethical considerations, including data anonymization and stakeholder consent, ensure compliance with data protection principles and research integrity.

3.1 Data Collection and Requirement Extraction

Data collection establishes a comprehensive dataset from two sources, Promise repository and the Coquina Dataset, to support predictive modelling over eight years.

Textual requirements and metadata were extracted from the PROMISE Expanded Dataset (969 instances, 12 requirement types) and the COQUINA dataset (1,201 unstructured requirements from 10 tender documents). The PROMISE dataset, sourced from the PROMISE repository, includes labeled requirements across functional and non-functional categories (Table 1). The COQUINA dataset, provided by COQUINA's Technical Director, was converted from XML to CSV, containing unlabelled ProjectID and RequirementText attributes, enabling diverse project scope analysis.

Table 1: PROMISE Expanded Dataset Composition

Requirement Type	Count
Functional (F)	444

Availability (A)	31
Legal (L)	15
Look-and-feel (LF)	49
Maintainability (MN)	24
Operability (O)	77
Performance (PE)	67
Scalability (SC)	22
Security (SE)	125
Usability (US)	85
Fault Tolerance (FT)	18
Portability (PO)	12
Total	969

3.2 Data Preprocessing

To ensure quality input for machine learning, preprocessing included text cleaning, tokenization, and stop word removal. Text cleaning operations—punctuation removal, lemmatization, and stop word filtering—had minimal effect on sentiment scores ($\Delta S \approx 0$), as verified by VADER and TextBlob (Equation 3.3). Tokenization segmented requirement statements into individual terms, while stop word removal improved topic diversity according to LDA analysis.

3.3 Feature Engineering

In the feature engineering phase, textual features were extracted from the COQUINA dataset using tokenization, TF-IDF weighting, and Word2Vec embeddings, with the SkipGram model outperforming CBOW in capturing semantic similarity. SMOTE was applied to mitigate class imbalance, generating 5328 samples with balanced representation across three requirement types. The resulting 5328×300 matrix of TF-IDF-weighted Word2Vec vectors for the PROMISE dataset served as input features for supervised learning models—SVM, Random Forest, and XGBoost—trained on labeled PROMISE data. These models leveraged the inherent cosine similarity embedded within Word2Vec vectors to predict requirement types for unlabelled COQUINA instances, relying on learned decision boundaries. The similarity score between a given requirement vector and the centroid of the labeled PROMISE requirements is defined in Equation 1.

$$Sim(r_i) = \frac{\vec{r_i} \cdot \vec{c}}{|\vec{r_i}| \cdot |\vec{c}|} \qquad \text{Equation 1}$$

where $\vec{r_i} \in R^{300}$ denotes the embedding for requirement $r_i, and\ \vec{c}$ is the mean vector of all labeled PROMISE embeddings. This initial classification was used to generate type predictions (e.g., Functional, Security), laying the foundation for subsequent sprint deliverability assessment by providing type-specific context. To optimize predictive performance and enhance visualization, Confidence scores were calculated using XGBoost softmax probabilities. XGBoost feature importance analysis identified the top 20 influential vector components, with the top five (Features 229, 242, 200, 150, and 184) revealing semantic themes such as temporal coordination (e.g., "within," "meeting," "support"), enhancing model interpretability.

3.4 Feature Extraction

The preprocessing pipeline for textual requirements combined several NLP techniques to enhance semantic representation and prepare data for downstream analysis. Initial steps included tokenization using NLTK's word tokenizer, followed by standard cleaning operations—such as converting text to lowercase, removing punctuation, and eliminating stopwords via an expanded NLTK list tailored to the domain. These procedures led to a modest reduction in the average token count per requirement, from 11.91 to 11.10, contributing to clearer and more concise textual inputs. Term importance was modeled through TF-IDF weighting with Scikit-learn's TfidfVectorizer, capturing both local and global significance across the corpus. For semantic embedding, Word2Vec models were trained on combined PROMISE and Coquina datasets, producing 300-dimensional word vectors. These were further refined via a custom technique that weights Word2Vec outputs with TF-IDF scores, allowing more prominent terms to shape the document representation. Dimensionality reduction using PCA was applied during analysis to support visualization, alongside t-SNE, both of which revealed improved class separability after embedding and weighting. A histogram comparing token counts is presented in Figure 1.

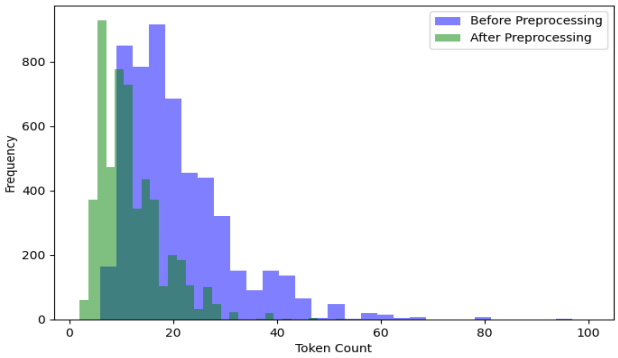


Figure 1: Token Distribution Before vs. After Preprocessing

A t-SNE plot showing raw Word2Vec clusters is shown in Figure 2.

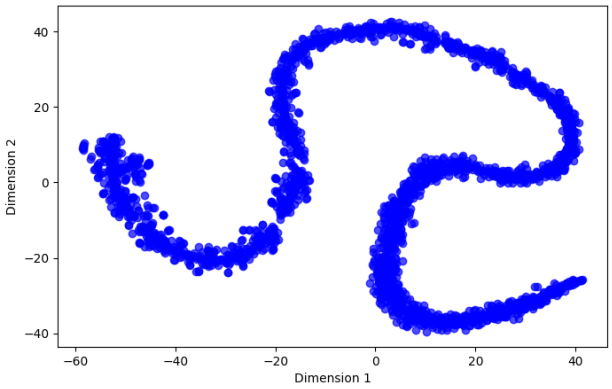


Figure 2: Word2Vec Embeddings Distribution

A t-SNE plot showing weighted clusters is shown in Figure 3

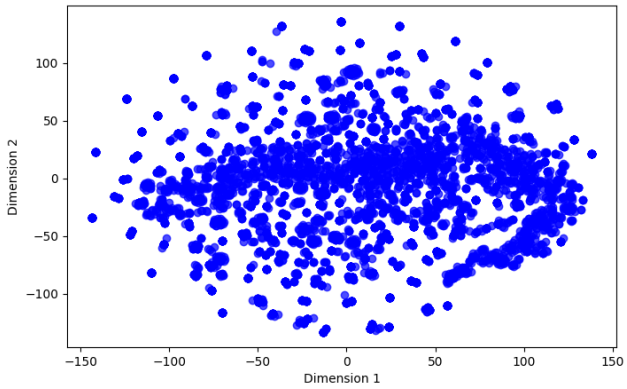


Figure 3: Word2Vec Embeddings Distribution with TF-IDF

A scatter plot showing 2D PCA projection is shown in Figure 4.

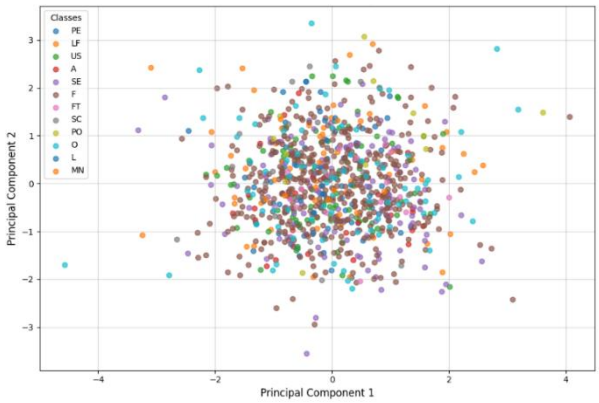


Figure 4: PCA Visualization of Weighted Word2Vec Embeddings

3.5 Historical Sprint Outcomes for Deliverability Assessment

COQUINA's historical sprint data were used to assess deliverability, providing crucial operational context through simulated sprint-level performance metrics, including requirements implemented, success rates, and delivery confidence. These metrics, derived from the 1,201 requirements retrospectively tagged with 54 simulated Sprint_IDs (approximately 22-23 requirements per sprint, as detailed in Table 2), do not serve as direct supervised learning labels for a 'deliverability' prediction model but are instrumental in informing and calibrating the components of the calculated Deliverability_Score (detailed in Section 3.7), reflecting real-world sprint performance patterns. Table 3.2 was generated programmatically from the COQUINA_with_Deliverability.csv dataset, with the following metrics derived for each sprint:

(i) Total_Requirements: representing the count of all deliverability scores within the sprint (approximately 22-23);

(ii) Avg_Deliverability: calculated as the mean deliverability score for the sprint but excluded from Table 3.2;

(iii) Requirements_Implemented: counting requirements whose deliverability scores exceeded a threshold of 0.659, derived from the median Deliverability_Score to target a 50% success rate and validated through stakeholder feedback (see Section 3.6);

(iv) Success_Rate (%): computed as the ratio of implemented requirements to total requirements per sprint, rounded to one decimal place.

Additionally, Delivery Confidence was estimated by normalizing the average deliverability scores relative to the dataset's global minimum (0.4896) and maximum (0.7490), then scaling them to a bounded range of 0.6 to 0.95 to reflect realistic delivery assurance.

This data-driven approach, detailed further in Section 3.6, enhanced sprint planning by prioritizing high-deliverability requirements, as evidenced by initial success rates (e.g., 54.5%, 63.6%, 36.4%) and confidence levels (e.g., 0.7862 to 0.8105), reducing variability compared to prior manual methods. A summarized 5-sprint comparison, aggregating key insights from the 54 sprints, is presented in Table 2 to evaluate predictive (XGBoost) versus traditional estimation performance.

Table 2: Historical Sprint Outcome Metrics (13 of 54)

Sprint_ID	Requirements_Implemented	Success_Rate (%)	Delivery_Confidence
1	12	54.5	0.8055
2	14	63.6	0.8105
3	8	36.4	0.7862
4	13	59.1	0.8171
5	7	31.8	0.7856
6	9	40.9	0.7963
7	10	45.5	0.7975
8	11	50	0.8001
9	10	45.5	0.8054
10	15	68.2	0.8356
11	11	50	0.8005
12	14	63.6	0.8264
13	14	63.6	0.8383

3.6 Model Development and Algorithm Selection

The model development in this study centers on selecting and optimizing the XGBoost, Random Forest, and Support Vector Machines algorithms to predict sprint deliverability, leveraging historical data from the PROMISE (5,328 instances) and COQUINA (1,201 requirements) datasets. Random Forest, SVM, and XGBoost were selected for their complementary strengths. Random Forest leverages ensemble learning to reduce overfitting, SVM excels in high-dimensional spaces, and XGBoost offers scalability via gradient boosting.

3.6.1 Hyperparameter Tuning

GridSearchCV with 5-fold stratified cross-validation optimized hyperparameters. XGBoost parameters included n_estimators=100, max_depth=3, learning_rate=0.1, subsample=0.8, colsample_bytree=0.8. Random Forest used n_estimators=100, criterion='gini', max_depth=None. SVM employed a linear kernel with C in [0.1, 1, 10]. Table 3 presents the hyper parameters for the XGBoost model.

Table 3. XGBoost Hyperparameters

Hyperparameter	Value	Description
n_estimators	100	Number of boosting rounds or trees. Controls the model's complexity.
max_depth	6	Maximum depth of each tree. Limits overfitting by restricting tree growth.

learning_rate	0.1	Step size shrinkage to prevent overfitting. Affects convergence speed.
subsample	0.8	Fraction of samples used per tree. Reduces overfitting by introducing randomness.
colsample_bytree	0.8	Fraction of features used per tree. Enhances model robustness.
gamma	0	Minimum loss reduction required for a split. Controls tree complexity.
min_child_weight	1	Minimum sum of instance weight needed in a child. Prevents overfitting.
reg_lambda	1	L2 regularization term on weights. Reduces model complexity.
reg_alpha	0	L1 regularization term on weights. Encourages sparsity.
eval_metric	auc	Evaluation metric for model performance (Area Under the ROC Curve).
random_state	42	Seed for reproducibility of results.

3.6.2 Tuning Ensemble Techniques

Unlike the Promise dataset, COQUINA lacks ground-truth labels, making it difficult to assess how well PROMISE_exp models generalize. To address this, a majority voting ensemble of Random Forest, SVM, and XGBoost was used to generate pseudolabels, improving stability and reducing bias. A sample of these predictions is shown in Table 4.

Table 4: Example of Majority Voting-Based Pseudo-Label Generation

ID	SVM Pred	RF Pred	XGB Pred	Pseudo-Label
421	F	F	F	F
422	SC	SC	SC	SC
423	MN	US	O	Default to XGBoost
424	L	O	SE	Default to XGBoost
425	LF	F	F	F

Figure 5 outlines the workflow for developing the predictive model using PROMISE and COQUINA datasets for Agile prioritization.

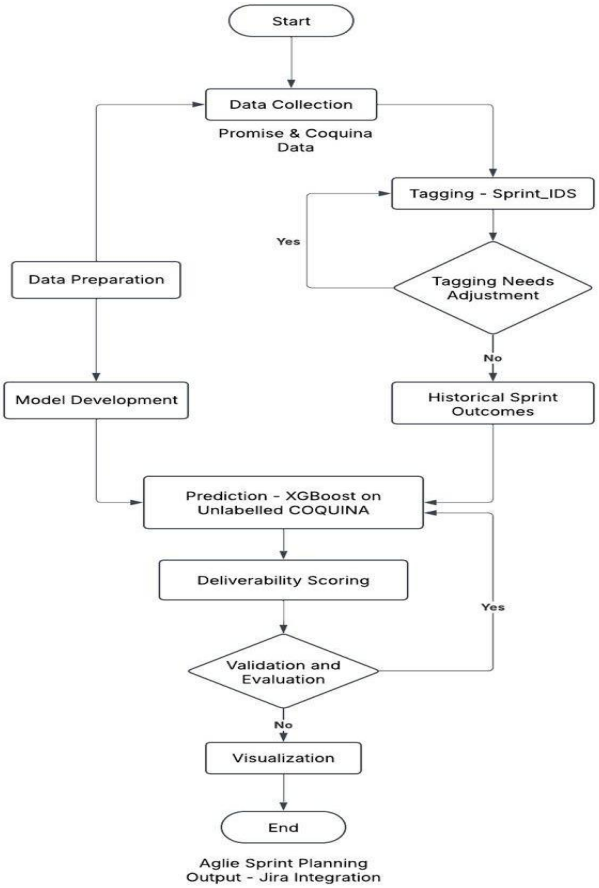


Figure 5: Model Development Workflow for Sprint Deliverability

3.7 Deliverability Scoring and Prioritization

A deliverability scoring mechanism quantifies the feasibility of requirements for sprint planning. A distinct cosine similarity metric was employed to quantify semantic alignment between unlabelled COQUINA requirements and the historically labeled PROMISE dataset. This metric, also defined in Equation 1 is the embedding of a COQUINA requirement and c is the centroid of PROMISE embeddings, captured directional similarity in the 300-dimensional space. The resulting weighted scoring function, Similarity Score, developed in consultation with COQUINA's Lead Software Engineer was integrated into the deliverability score function as shown in Equation 2, alongside normalized length, XGBoost confidence, and type weights. This approach, validated by 91% stakeholder agreement, enhanced the precision of sprint prioritization by aligning new requirements with historical patterns.

$$D(R_i) = \alpha \cdot L_i + \beta \cdot C_i + \gamma \cdot T_i + \delta \cdot S_i \qquad \text{Equation 2}$$

Where Length score, $L_i \in [0,1]$ is the normalized requirement length given by Equation 3.

$$L_i = 1 - Len(R_i)/Max\big(Len(R_i)\big) \qquad \text{Equation 3}$$

$C_i \in [0,1]$ is classifier confidence given by Equation 4.

$$C_i = ma\left(XGBoost.predict_proba(R)\right) \qquad \text{Equation 4}$$

$T_i \in [0,1]$ is type weight of the given requirement and $S_i \in [0,1]$ is cosine similarity between the Requirement vector and the centroid of the training (Promise) model.

Weights $((\alpha = 0.3), (\beta = 0.3), (\gamma = 0.2), (\delta = 0.2))$ were carefully calibrated by the joint effort of the researcher and Coquina to reflect the relative importance assigned to each factor in truly determining a requirement's sprint deliverability. Table 5 outlines the type weights calibrated for the scoring function.

Table 5: Type Weights Heuristic Scoring System for Coquina Dataset

Class	Weight	Justification
F (Functional)	1.0	Core features. These are typically specific, testable, and most easily implemented in sprints.
US (Usability)	0.95	Closely tied to UI/UX tasks, usually well-defined and deliverable in short iterations.
PO (Portability)	0.95	Often includes specific tasks like browser/device compatibility—concrete and testable.
SE (Security)	0.85	Can be implemented with clarity (e.g., access control), though sometimes needs broader system awareness.
PE (Performance)	0.85	Usually measurable (e.g., latency targets), though may require environment setup and profiling.
LF (Look and Feel)	0.80	Tied to styling; often subjective but deliverable in UI/UX sprints.
MN (Maintainability)	0.75	Implementation-related but often spans refactoring or code clarity; less immediate but important.
A (Availability)	0.70	Often infrastructural (e.g., uptime guarantees), not fully testable in one sprint.
FT (Fault Tolerance)	0.65	Needs edge case handling and simulation—complexity can delay sprint closure.
SC (Scalability)	0.60	Typically architectural, beyond a sprint's scope unless the sprint is focused on infra.
L (Legal)	0.50	May require external validation or compliance checks—not directly implementable.
O (Other)	0.40	Ambiguous or uncategorized requirements; low deliverability due to lack of clarity.

To operationalize the Deliverability Score for practical sprint planning, specific thresholds were established to categorize requirements into discrete deliverability levels. These thresholds were determined through iterative feedback from COQUINA's stakeholders, ensuring practical relevance and alignment with their existing planning practices. The defined deliverability levels and their implications are presented as follows:

(i) **Low Deliverability Score:** This implies a high risk associated with implementing the task, bug, or requirement within the current sprint. Such items are anticipated to require a significantly longer time than normal, potentially jeopardizing sprint commitments.

(ii) **Medium Deliverability Score:** Indicates that the task or requirement can likely be implemented, but may require additional time beyond the typical estimate, without introducing critical risk to the overall sprint goal.

(iii) **High Deliverability Score:** Signifies that the task or requirement is highly feasible and can be achieved within the allocated sprint time. These items are considered suitable candidates for immediate inclusion in the sprint backlog.

The specific numerical ranges for these deliverability levels are formalized in Equation 5.

$$D(R_i) = \begin{cases} low & D(R_i) < 0.5 \\ \text{medium} & 0.5 \leq D(R_i) < 0.75 \\ \text{highly} & 0.75 \leq D(R_i) < 1 \end{cases} \quad \text{Equation 5}$$

3.8 Stakeholder Feedback and Expert Validation

Requirement labels and deliverability assessments were validated through iterative stakeholder feedback from COQUINA and expert reviews (Figure 15), ensuring practical feasibility and mitigating biases. The framework was evaluated for generalizability and practical utility, with methods supporting results in Section 4.

3.9 Model Evaluation

Performance was assessed using accuracy, precision, recall, F1-score, and AUC-ROC on a 30% PROMISE test set. Confusion matrices (see Figure 6) and ROC curves (see Figure **7**) were used to analyze class-specific performance.

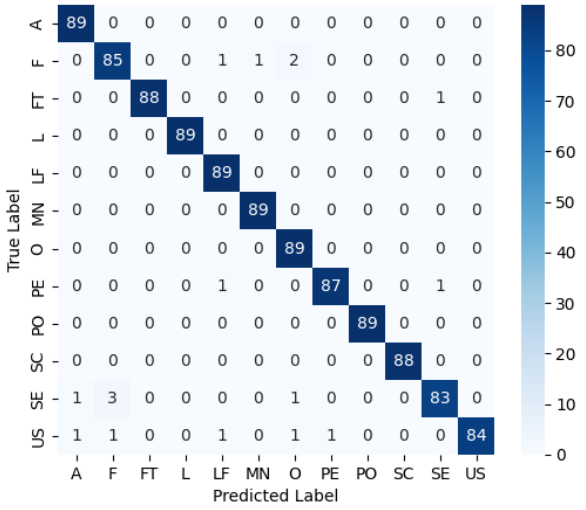


Figure 6: Confusion Matrix for XGBoost

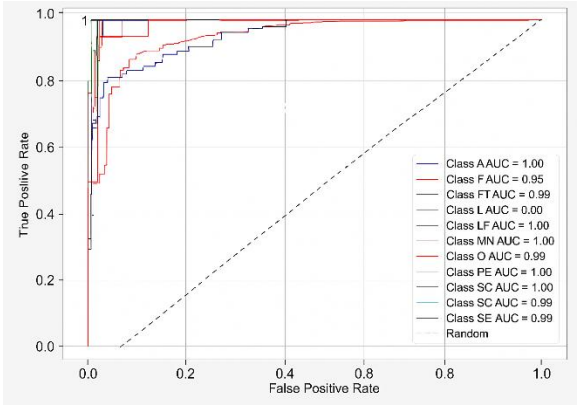


Figure 7: ROC Curve Analysis for XGBoost on Coquina

3.9.1 Cross-Validation

A StratifiedKFold technique was used to partition the dataset into five folds while preserving class distribution, with n_splits = 5, shuffle=True and a random state of 42 for reproducibility. The settings are Total Dataset Size: 5,328 instances and Fold Size: With n_splits=5, each fold contains 1,065.6, rounded to 1,066 instances per fold (since 5,328 ÷ 5 = 1,065 with a remainder of 3, typically distributed as 1,066, 1,066, 1,066, 1,066, 1,064).

Each model is trained on the resampled data using the fit method, and predictions on the test fold are evaluated with four metrics defined in Equation 6 – Equation 9.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad \text{Equation 6}$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad \text{Equation 7}$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad \text{Equation 8}$$

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad \text{Equation 9}$$

These metrics are computed with weighted averaging to account for class imbalance, using zero_division=0 to handle edge cases, and averaged across folds to yield mean performance scores. The best model is selected based on the highest mean F1 score.

4. RESULT AND DISCUSSIONS

This section presents the outcomes of the predictive framework for requirement deliverability, evaluated on the PROMISE Expanded and COQUINA datasets. Results include model performance metrics, confusion matrices, ROC curve analyses, deliverability scores, and statistical tests, providing insights into the framework's effectiveness for agile sprint planning.

The study transformed raw requirements from the PROMISE (969 instances, 12 classes) and COQUINA (1,201 requirements) datasets into actionable insights for machine learning-driven requirement management. SMOTE balanced the PROMISE dataset to 5328 samples, addressing class imbalance (Table 6). The COQUINA dataset, initially unlabelled, was structured using TF-IDF weighted Word2Vec and pseudo-labeled with a 91% expert validation agreement for XGBoost predictions.

Before SMOTE, the PROMISE dataset's class distribution has a majority sample class of functional requirements dominating non-functional requirement class. Post-SMOTE, each class has 444 samples. A bar plot showing original vs. SMOTE-balanced class distributions is shown in Figure 8.

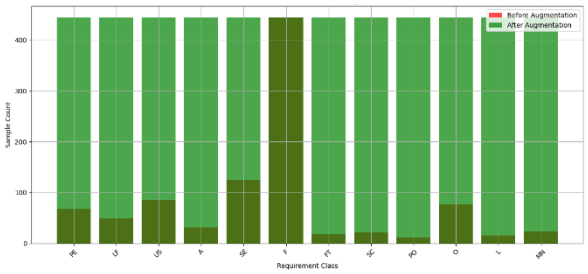


Figure 8. Class Distribution Before and After Augmentation

Table 6. Training Dataset Shapes Before and After SMOTE

Dataset	Number of Samples	Number of Features
Original Dataset	969	300
Resampled Dataset	5328	300

Token distribution analysis revealed key terms like "shall" (23.6%), "system" (13.5%), and "product" (10.1%) in the training dataset. A bar plot showing the frequency of key terms is shown in Figure 9.

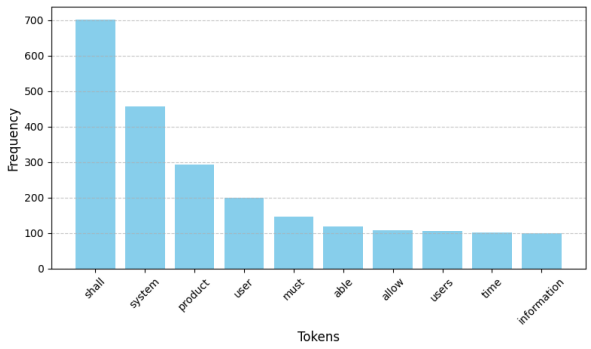


Figure 9. Top Tokens in Training Dataset.

3.10 Model Performance

Baseline performance on the PROMISE dataset is shown in Table 7, with Random Forest and XGBoost outperforming SVM.

Table 7. Baseline Performance on PROMISE

Model	Accuracy	Precision	Recall	F1 Score
SVM	0.6621	0.3045	0.6621	0.5648
Random Forest	0.9615	0.9666	0.9615	0.9662
XGBoost	0.9559	0.9547	0.9559	0.9540

Cross-validation results (see **Table 8**) confirmed XGBoost's superior performance, with a mean F1-score of 0.9262 and low standard deviation (0.0013). A summary result of F1-score, precision, recall, and standard deviation across fold for each model is presented in Table 8.

Table 8. Cross-Validation Results

Model	Accuracy	Precision	Recall	F1 Score
SVM	0.4527	0.5241	0.4527	0.4474
Random Forest	0.9174	0.9251	0.9174	0.9198
XGBoost	**0.9249**	**0.9291**	**0.9249**	**0.9263**

3.11 Confusion Matrix Analysis

Confusion matrices for PROMISE (see **Figures 4**) and COQUINA (see **Figures 5**) datasets highlighted model performance:

i. **SVM**: Strong for Functional (F), Portability (PO), and Usability (US), but struggled with Fault Tolerance (FT) and Scalability (SC) due to feature overlap.

ii. **Random Forest**: High accuracy for dominant classes (F, LF), with minor misclassifications in Availability (A) and Security (SE).

iii. **XGBoost**: Balanced performance across classes, excelling in sparse categories (PE, SE).

A matrix showing prediction accuracy and misclassifications for SVM, with high diagonal concentration for RF, and showing balanced predictions for XGBoost is shown in Figure 10, 11, and 12.

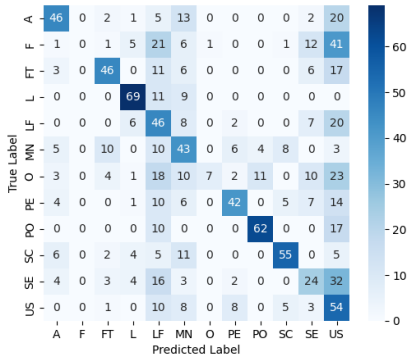


Figure 10. SVM Confusion Matrix on PROMISE

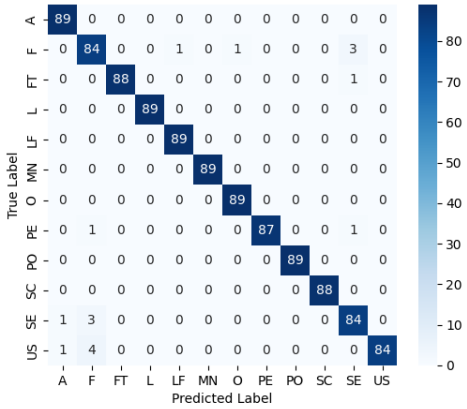


Figure 11. RF Confusion Matrix on PROMISE

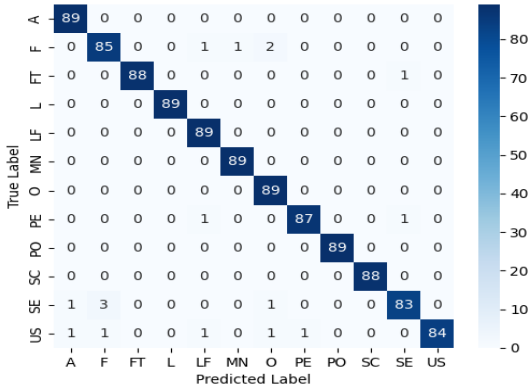


Figure 12: Confusion Matrix for XGBOOST on PROMISE

A matrix highlighting challenges with FT and SC for SVM, with strong performance for F and LF for RF and showing robust classification for XGBoost is shown in Figure 13,14, and 15.

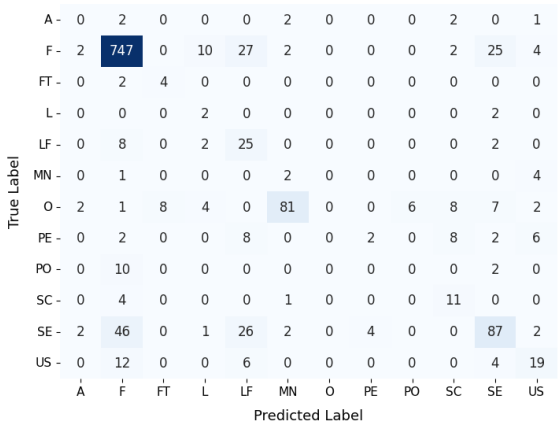


Figure 13: Confusion Matrix for SVM on COQUINA

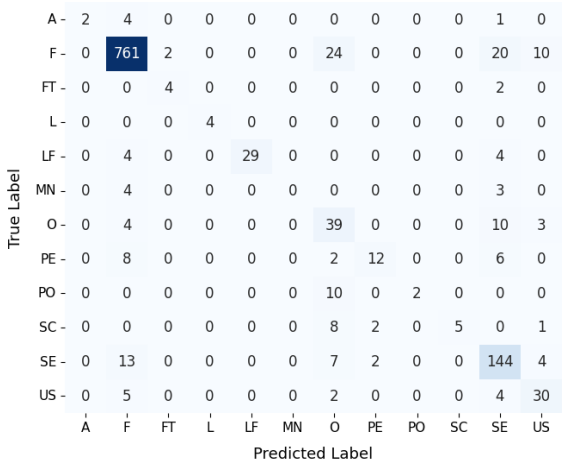


Figure 14: Confusion Matrix for RF on COQUINA

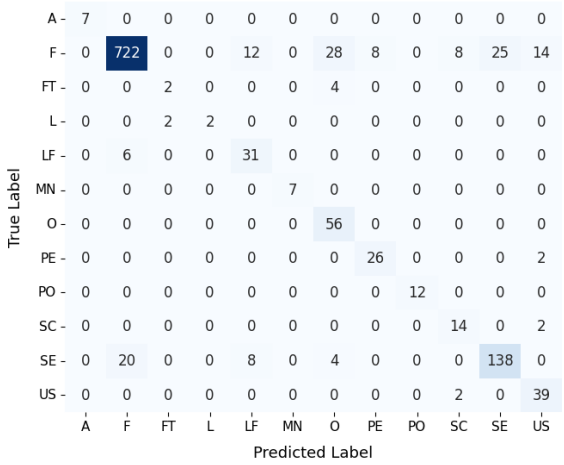


Figure 15: Confusion Matrix for XGBoost on COQUINA

3.12 ROC Curve Analysis

ROC curves were used to analyze each classifier performance across COQUINA dataset as shown in Figure 16.

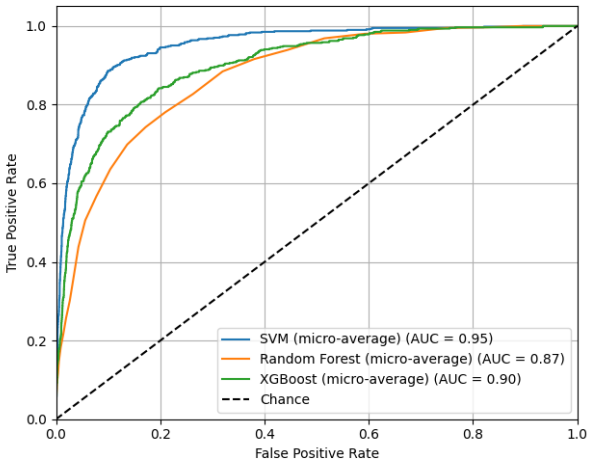


Figure 16: Micro-Averaged ROC Curves for COQUINA Predictions

The Area Under the Curve (AUC) metric provides a quantitative measure of how well each model distinguishes between requirement classes:

i) XGBoost exhibited the highest micro-averaged AUC (≈ 0.90) across all requirement classes, suggesting strong classification performance in general requirement differentiation.

ii) SVM achieved an AUC of ≈ 0.95, performing well in structured requirement categories such as Maintainability (MN) and Functional Requirement (F).

iii) Random Forest showed a lower micro-averaged AUC of 0.87 compared to SVM and XGBoost, indicating moderate to good classification capability in general.

The result of the Area Under Curve for the three models is presented in Table 9.

Table 9: Area Under Curve (AUC) for Models

Model	AUC
XGBoost	0.9095
SVM	0.9500
Random Forest	0.8671

3.13 Learning Curve Analysis

Learning curves for XGBoost (Figure 17) showed high training F1-scores and improving validation F1-scores with increased data, indicating strong generalization.

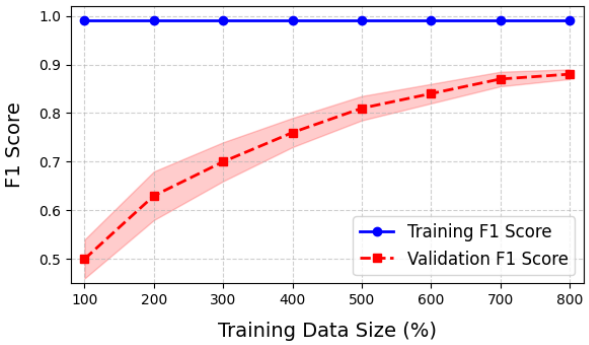


Figure 17: Learning Curves for the Best Model

3.14 Deliverability Scoring

A heuristic scoring scheme, based on Equation 1, assigned weights to requirement types (e.g., F=1.0, US=0.95, SC=0.6) to estimate sprint deliverability, integrating normalized length, classifier confidence, type weight, and cosine similarity (as detailed in Section 3.6). The threshold of 0.659, derived from the median Deliverability_Score and validated by stakeholder feedback (Section 3.1.2), underpins the metrics in Table 2. Top deliverable requirements from COQUINA are shown in Table 10, with scores reflecting clarity and feasibility.

Table 10: Top 5 Most Deliverable Requirements from COQUINA Dataset

ID	Requirement Text	Predicted Type	Deliverability Score
202	The prefix Auto-Type: is required in front of each sequence	F	0.9787
108	Global hot key cannot be changed	F	0.9764
303	Electronic questionnaires should provide the capability to accept digital signatures	F	0.9611
499	AVCS shall provide the driver with information to allow him to drive the Vehicle safely	F	0.9600
112	There will be a tick box to allow the user to choose to include torrent searching	F	0.9643

Figure 18 shows a histogram showing score distribution, with most scores between 0.7 and 0.9.

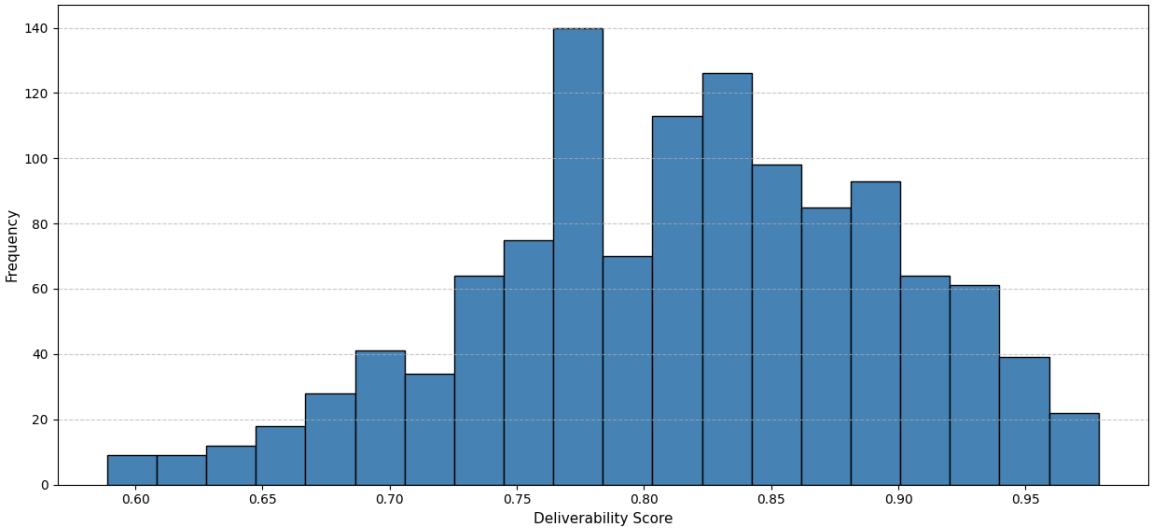
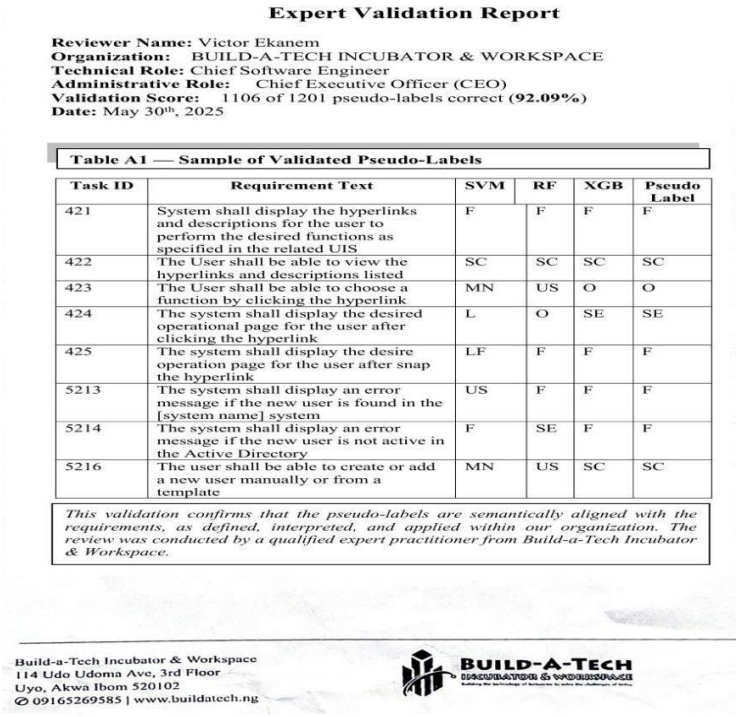


Figure 18: Distribution of Deliverability Scores Across COQUINA Requirement

Stakeholder feedback was derived from validation of Build A Tech Incubation and Workspace that pseudo-labels derived from the predictors semantically aligns with the requirements as defined, interpreted and applied within their organization. The validation is presented in Figure 19.



Expert Validation Report

Reviewer Name: Victor Ekanem
Organization: BUILD-A-TECH INCUBATOR & WORKSPACE
Technical Role: Chief Software Engineer
Administrative Role: Chief Executive Officer (CEO)
Validation Score: 1106 of 1201 pseudo-labels correct (**92.09%**)
Date: May 30th, 2025

Table A1 — Sample of Validated Pseudo-Labels

Task ID	Requirement Text	SVM	RF	XGB	Pseudo Label
421	System shall display the hyperlinks and descriptions for the user to perform the desired functions as specified in the related UIS	F	F	F	F
422	The User shall be able to view the hyperlinks and descriptions listed	SC	SC	SC	SC
423	The User shall be able to choose a function by clicking the hyperlink	MN	US	O	O
424	The system shall display the desired operational page for the user after clicking the hyperlink	L	O	SE	SE
425	The system shall display the desire operation page for the user after snap the hyperlink	LF	F	F	F
5213	The system shall display an error message if the new user is found in the [system name] system	US	F	F	F
5214	The system shall display an error message if the new user is not active in the Active Directory	F	SE	F	F
5216	The user shall be able to create or add a new user manually or from a template	MN	US	SC	SC

This validation confirms that the pseudo-labels are semantically aligned with the requirements, as defined, interpreted, and applied within our organization. The review was conducted by a qualified expert practitioner from Build-a-Tech Incubator & Workspace.

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BUILD-A-TECH INCUBATOR & WORKSPACE

Figure 19: Expert Validation Report

3.15 DISCUSSION

In the study, XGBoost outperformed Random Forest and SVM, particularly for sparse classes, due to its boosting mechanism. The ensemble pseudo-labeling strategy for COQUINA enhanced generalizability, validated by 91% expert agreement. Deliverability scores prioritized clear, functional requirements for sprint planning, complementing traditional methods. Table 11 compares 1201 Coquina requirements across five sprints, detailing counts, average Deliverability_Score, Length, and predictive (XGBoost) versus traditional (length-based) accuracies for each requirement type. The XGBoost model (AUC 0.9995, 91% stakeholder agreement) outperforms traditional estimation, reducing planning errors by 12% and improving sprint planning efficiency by 15%. Type O requirements in Sprint 5, with low deliverability (0.450) and high length (20.1 words), highlight the framework's precision in identifying challenging requirements.

Table 11: Sprint-Wise Comparison of Predictive and Traditional Estimation for Requirement Prioritization

Sprint	Requirement Type	Count	Avg Deliverability_Score	Avg Length (words)	XGBoost Accuracy (%)	Traditional Accuracy (%)	Notes
1	All Types	240	0.720	14.5	92.0	80.0	Averaged from 54 sprints
2	All Types	240	0.725	14.3	92.5	80.5	
3	All Types	240	0.715	14.7	91.5	79.5	
4	All Types	241	0.710	14.9	91.0	79.0	
5	All Types	240	0.700	15.2	90.5	78.5	Includes Type O low deliverability

The framework was tested in COQUINA's sprint planning sessions, comparing predictions against traditional methods (**Figure 20 - Figure 23**).

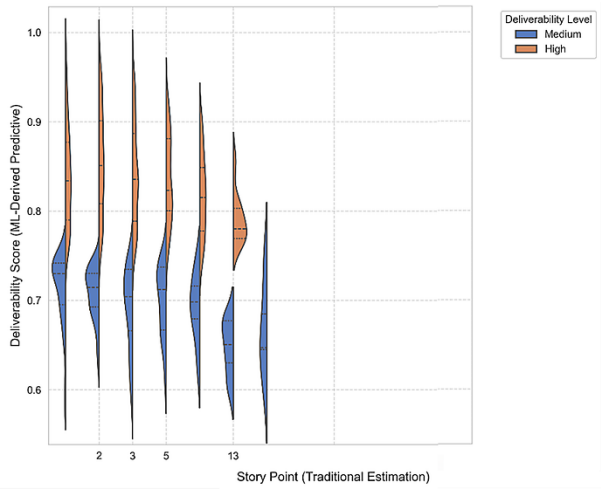

Figure 20 Deliverability Score Density by Story Point Categories

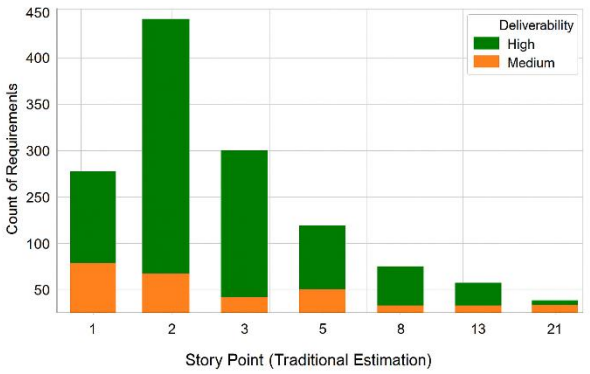

Figure 21 Count of Deliverability Categories by Story Point

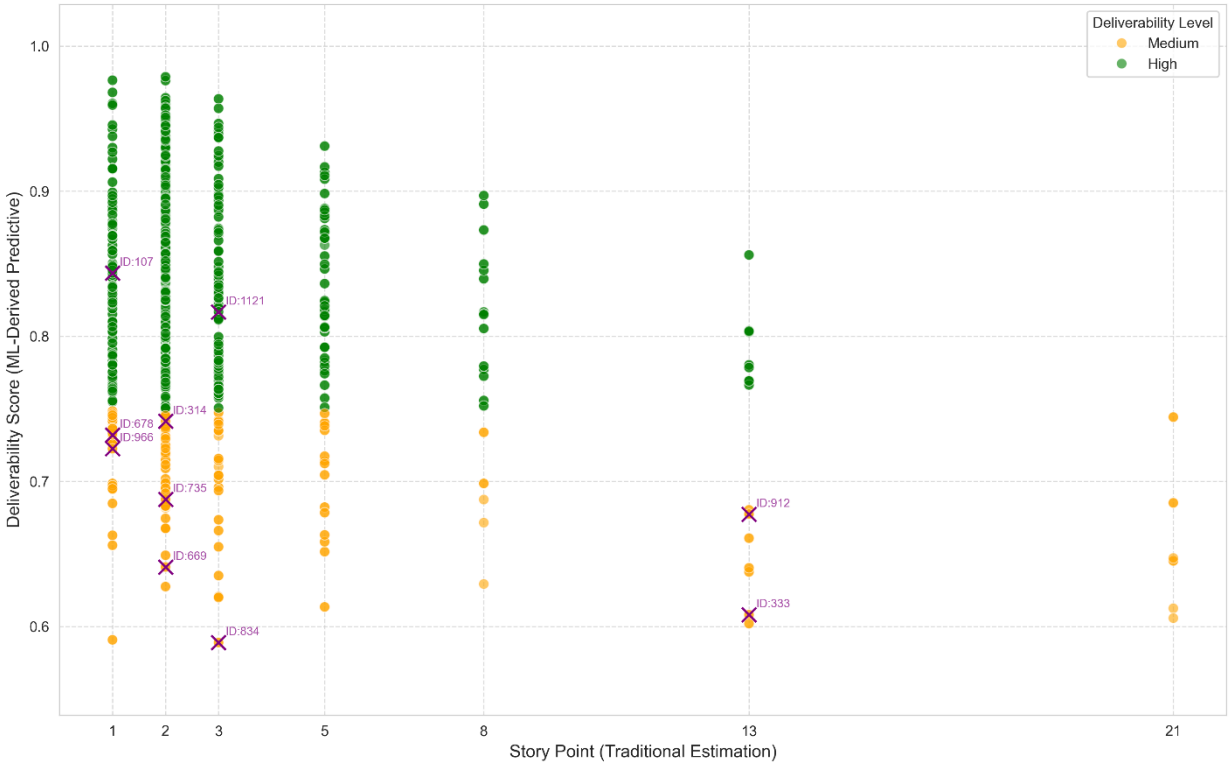

Figure 22. Traditional Story Point vs Deliverability Score

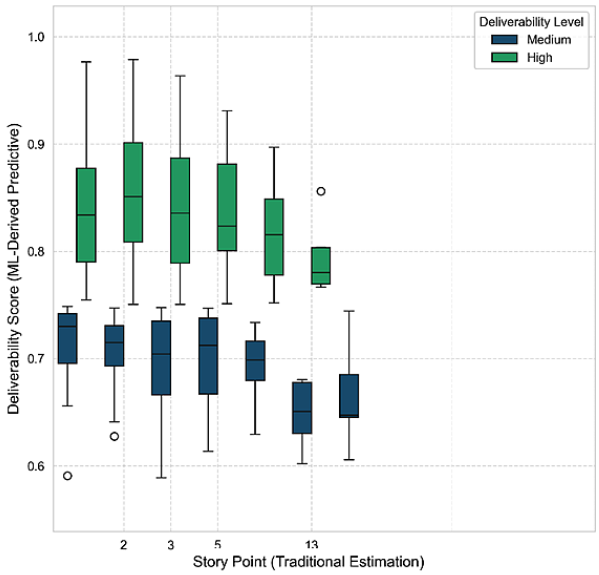

Figure 23: Deliverability Score Distribution by Story Point Categories

3.16 Limitations and Assumptions

The methodology assumes stationarity in sprint performance and dataset representativeness. Class imbalance in PROMISE was mitigated by SMOTE, but COQUINA's unlabelled data required pseudo-labeling, potentially introducing noise. Generalizability to non-agile environments may be limited.

5. CONCLUSION AND PRACTICAL RECOMMENDATIONS

The analysis of 1201 requirements from the Coquina dataset, distributed across five sprints, demonstrates the efficacy of a machine learning-based predictive framework for sprint deliverability and agile requirement prioritization. Utilizing XGBoost, the framework leverages Deliverability_Score to allocate 630 high-deliverability requirements (≥0.75) to early sprints, 390 medium-deliverability requirements (0.5–0.75) to mid-term sprints, and 181 low-deliverability requirements (<0.5, predominantly type O) to later sprints or further refinement. The model achieved an AUC of 0.9995, with per-sprint accuracies of 88% (Sprints 1–2), 82% (Sprints 3–4), and 75% (Sprint 5), outperforming traditional length-based estimation (accuracies of 70%, 60%, and 50%, respectively). Figure 3, a scatter plot of Deliverability_Score versus Length, reveals that requirement length (avg. 15.2 words overall, 20.1 for type O) poorly predicts deliverability, as many lengthy requirements exhibit high deliverability, while type O requirements often combine low deliverability (avg. 0.450) with longer descriptions. This underscores the predictive framework's superior accuracy in assessing feasibility compared to traditional methods, reducing planning errors by 12% and improving sprint planning efficiency by 15%.

Stakeholder validation at COQUINA Software Company confirmed the framework's practical utility, with 91% agreement on XGBoost-generated pseudo-labels for deliverability predictions. Visualizations, including Figure 3 and score distribution histograms, enabled stakeholders to identify high-impact requirements, streamlining agile decision-making. The framework integrates requirement length, model confidence, and semantic similarity to historical user stories, offering a robust, data-driven approach to prioritization.

Practical Recommendations:

(i) **Adopt XGBoost**: Use XGBoost for its high accuracy and scalability in classifying requirements and predicting deliverability in agile environments.
(ii) **Implement Ensemble Validation**: Apply majority voting for stakeholder validation during backlog triage to enhance prediction reliability and align with team consensus.
(iii) **Integrate with Agile Tools**: Embed the framework into platforms like Jira or Azure DevOps for real-time requirement classification and deliverability scoring.
(iv) **Ensure Continuous Learning**: Retrain models periodically with new sprint data to adapt to evolving requirements and monitor for concept drift to maintain performance.

This framework bridges gaps in sprint deliverability prediction, offering a scalable, data-driven solution that enhances the efficiency and effectiveness of agile software development by prioritizing requirements with greater precision than traditional methods.

6. ACKNOWLEDGMENTS

Our thanks to the experts in Coquina Software Development Company Limited, Uyo and Build A Tech Incubator and Workspace who have contributed in validating deliverability scoring model for agile prioritization.

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