

Predictive Analytics for Loan Default risk using machine learning and real time financial streams

Clifford Shearing

Lead Mentor

Abstract:

Credit risk assessment has moved beyond static scoring to real-time, data-driven analytics. By integrating diverse data (transactions, behavior, macroeconomic factors), modern ML models continuously evaluate borrower creditworthiness, enabling early warnings of default. Compared to legacy methods, this approach yields substantial predictive gains. We compare several classifiers—logistic regression, SVM, decision trees, random forest, and XGBoost—for loan default prediction. Ensemble tree-based methods consistently outperform others, delivering higher accuracy, precision, and F1 scores. In particular, Random Forest achieved the highest predictive performance, showing strong F1 and precision in identifying risky loans. Across metrics (accuracy, recall, AUC), this ensemble approach surpasses simpler models, as benchmarks confirm. Notably, one study found Random Forest anticipated ~12.7% of high-risk client transitions early and helped avert ~67.6% of potential losses. These findings suggest that a Random Forest-based model provides the most reliable credit-risk forecasts, enhancing decision-making and enabling cost savings in risk management. Crucially, these predictive improvements reinforce evidence-based lending: advanced ML models are noted to instill greater confidence in lenders by providing data-driven insights. By reducing misclassification of risky loans, they directly translate into cost savings and stronger overall financial stability. Ultimately, our results demonstrate that choosing the right ML model is key to robust credit risk management.

1. Introduction

The stability of financial institutions and the broader economy depends heavily on their ability to manage credit risk effectively. Loan default, defined as the failure of a borrower to meet repayment obligations, poses one of the most significant threats to banking profitability and financial stability. Traditional methods of assessing creditworthiness have relied largely on static indicators such as credit history, income statements, and financial ratios. While useful, these indicators often fail to capture the dynamic nature of borrower behavior and evolving economic conditions. The emergence of real-time financial transaction data streams—including credit card usage, bank transfers, payroll deposits, and even digital wallet activity—has transformed the potential for credit risk modeling. By leveraging these continuous data flows, lenders can shift

from periodic, reactive evaluations to proactive, dynamic monitoring of borrower risk profiles [1]; [7].

1.1 Limitations of Traditional Approaches

Conventional credit scoring systems, such as FICO or bureau-based models, often suffer from latency and incompleteness. They rely on aggregated historical data that may not reflect a borrower's current financial condition. For example, a borrower facing sudden income disruption or rapid spending escalation may still appear creditworthy until the next bureau update. This lag introduces blind spots that increase the likelihood of unexpected defaults. Moreover, such models are constrained in their ability to integrate heterogeneous data sources such as real-time spending behavior, mobile payment activity, or alternative financial signals [10]. Consequently, lenders increasingly seek adaptive, data-driven frameworks capable of capturing both long-term patterns and short-term anomalies in borrower behavior.

1.2 Rise of Machine Learning in Credit Risk

Machine learning (ML) provides powerful tools for predictive analytics in finance, offering the ability to learn non-linear relationships, detect hidden patterns, and improve predictive performance over traditional statistical models. Early applications of ML in consumer credit risk demonstrated notable gains in accuracy over logistic regression and rule-based systems [11]. Since then, research has expanded across various algorithmic families, including decision trees, ensemble methods, support vector machines (SVM), and deep learning approaches [20]; [4].

Each model family offers advantages and limitations. Logistic regression is interpretable but struggles with high-dimensional, non-linear interactions. SVMs handle complex boundaries well but require intensive parameter tuning and lack scalability for large, streaming datasets. Deep neural networks show promise in modeling sequential patterns such as transaction streams, yet their opacity and computational demands present challenges for real-time risk scoring [8].

1.3 Comparative Advantage of Ensemble Models

Among the available techniques, ensemble learning methods, particularly Random Forest and gradient boosting frameworks (such as XGBoost), consistently achieve superior performance across credit risk prediction benchmarks. Random Forest combines multiple decision trees to mitigate overfitting and increase robustness, while gradient boosting optimizes residual errors sequentially for heightened accuracy. Studies highlight that ensemble classifiers often outperform both linear models and single-tree methods when applied to loan default prediction [9]; [16].

Importantly, Random Forest has demonstrated particular effectiveness in financial risk tasks because of its ability to handle large, heterogeneous datasets, accommodate missing values, and provide interpretability through feature importance rankings. In comparative analyses, Random Forest often surpasses gradient boosting in stability and ease of deployment for real-time systems

[14]. Moreover, its architecture can be adapted for online learning extensions, allowing incremental model updates as new transaction streams arrive, thereby ensuring that predictions remain current without complete model retraining.

1.4 Real-Time Financial Streams as a Game-Changer

The integration of real-time financial transaction streams with ML-based predictive analytics introduces a paradigm shift in credit risk management. Rather than waiting for periodic reporting, lenders can continuously monitor borrower activity and recalibrate risk scores dynamically. For instance, unexpected overdraft frequencies, sudden income declines, or spikes in discretionary spending can serve as immediate indicators of financial stress. Machine learning models trained on such streaming data can generate timely alerts, enabling banks to intervene before defaults occur [11]; [21].

This continuous monitoring framework also aligns with regulatory emphasis on stress testing and proactive risk mitigation. By embedding real-time predictive models into lending platforms, institutions can not only improve default detection but also optimize capital allocation, enhance customer segmentation, and offer tailored repayment plans. In turn, these practices contribute to overall financial resilience [13].

1.5 Why Random Forest Is the Preferred Model

While several machine learning models exhibit potential in predictive risk analytics, Random Forest emerges as the most suitable for this research due to its balance of predictive power, interpretability, and adaptability. Unlike deep neural networks, it does not require massive computational resources for training and inference, making it feasible for real-time deployment. Compared to logistic regression and SVMs, Random Forest better captures complex, non-linear borrower behaviors inherent in transactional data. Additionally, its feature importance outputs provide transparency, a critical factor for compliance in regulated financial environments [17]; 21.

Empirical studies underscore these advantages. [14] found Random Forest outperformed logistic regression in banking datasets, while [12] demonstrated its superior accuracy in loan application prediction tasks. Real-world evidence further suggests that Random Forest can reduce misclassification of risky loans, lower potential losses, and enable early interventions [22]. Thus, the current paper positions Random Forest not only as a technically effective model but also as a practically deployable solution for dynamic loan default prediction.

1.6 Contribution of This Study

This paper builds upon existing literature by integrating three key dimensions: (1) real-time financial streams as the primary data source, (2) a comparative evaluation of machine learning models for loan default prediction, and (3) the identification of Random Forest as the optimal model for balancing performance and operational feasibility. Through this framework, we argue

that Random Forest provides the best combination of predictive accuracy, transparency, and scalability for lenders seeking to proactively manage credit risk.

By advancing the use of machine learning in conjunction with real-time data, this study contributes to ongoing efforts to enhance financial stability, reduce default-related losses, and create more resilient lending systems. Ultimately, the work demonstrates how predictive analytics can empower financial institutions to transition from static, retrospective evaluations toward adaptive, real-time credit risk management—a critical evolution in the era of digital finance.

2. Literature Review

2.1 Evolution of Credit Risk Assessment

Traditional credit risk modeling relied on statistical techniques such as logistic regression and discriminant analysis. These methods were interpretable and simple to deploy, but their predictive power was limited in handling non-linear borrower behavior and high-dimensional data [1]. The limitations of these conventional tools led to the adoption of machine learning (ML), capable of capturing complex interactions and incorporating a wide array of features including behavioral and transactional data.

2.2 Role of Real-Time Data in Loan Default Prediction

Real-time financial streams are transforming risk assessment. Unlike credit bureau reports, which are updated periodically, real-time transaction data (e.g., card spending, salary deposits, transfers) provide continuous borrower behavior signals. [3] argue that embedding ML algorithms within real-time monitoring systems enhances financial stability by identifying early warning signs of distress. Similarly, [8] emphasizes the operational advantage of real-time data integration, enabling lenders to recalibrate risk scores dynamically.

[16] adds that cloud computing and big data platforms make real-time integration feasible at scale, particularly for financial institutions handling millions of customers. Together, these studies highlight that real-time analytics bridges the gap between static credit assessments and dynamic borrower realities.

2.3 Machine Learning Models in Credit Risk Prediction

A wide spectrum of ML algorithms has been applied to loan default prediction:

- **Logistic Regression:** Provides interpretability but struggles with non-linear data. Still widely used as a benchmark [2].
- **Support Vector Machines (SVM):** Effective with complex decision boundaries but computationally expensive for large datasets [5].

- **Decision Trees:** Easy to interpret but prone to overfitting.
- **Random Forest:** Robust ensemble method mitigating overfitting, offering superior accuracy and feature interpretability [9].
- **Gradient Boosting (XGBoost, LightGBM):** Often outperform Random Forest in static datasets but require careful tuning, and can be less stable in streaming environments [17].
- **Deep Learning (LSTM, DNNs):** Suitable for sequential data streams but less transparent, making them challenging in regulated industries [13].

The literature consistently shows that **ensemble methods** outperform simpler models and provide a balance between accuracy and operational feasibility.

2.4 Justification for Random Forest as the Best Model

Among ensemble methods, Random Forest has demonstrated consistent superiority in loan default prediction. [5] found that Random Forest outperformed logistic regression and SVM in predicting defaults across loan application datasets. [9] also reported stronger accuracy and stability with Random Forest compared to traditional techniques in banking contexts.

Random Forest's strengths include:

- Handling **high-dimensional and noisy datasets** [10].
- Generating **feature importance rankings**, aiding explainability [20].
- Adapting to **streaming environments** with incremental learning [17].
- Reduced **overfitting risk** compared to single decision trees [14].

[8] suggest that while gradient boosting may provide marginally higher accuracy in some contexts, Random Forest strikes a better balance between interpretability, stability, and real-time deployability—critical attributes for lenders operating under regulatory scrutiny.

2.5 Industry and Academic Perspectives

From an academic standpoint, predictive analytics has moved beyond accuracy metrics to also consider economic impact. Studies now evaluate cost savings from reduced misclassification of risky borrowers, enhanced capital allocation, and improved loan portfolio quality. Industry adoption is also accelerating as open banking initiatives make real-time transaction data accessible. Financial institutions increasingly view AI-driven predictive systems not only as risk tools but as strategic enablers of sustainable growth.

2.6 Research Gap and Contribution

Despite substantial progress, gaps remain. Much of the existing literature emphasizes retrospective datasets rather than live, streaming data. Additionally, comparative studies often

neglect real-time adaptability when evaluating model performance. This research addresses these gaps by:

1. Integrating real-time transaction streams into the predictive framework.
2. Conducting a comparative model evaluation based on standard metrics (accuracy, AUC, F1-score).
3. Identifying Random Forest as the optimal balance of accuracy, interpretability, and scalability for proactive loan default prediction.

By situating Random Forest within a real-time analytics context, this study advances both the theoretical understanding and the practical application of machine learning in credit risk management.

Reference	Focus	Methodology/Models	Key Findings	Relevance to Study
Adams & Owen (2022)	Real-time credit risk monitoring	Advanced ML + data analytics on live streams	Real-time monitoring enhances stability by detecting early warning signals	Validates need for real-time data integration
Chouksey et al. (2021)	Loan default prediction	Compared ML models incl. Random Forest, logistic regression, SVM	Random Forest outperformed others in predictive accuracy	Supports Random Forest as best-performing model
Shaheen & ElFakharany (2018)	Loan default in banking	ML models on banking datasets	ML > traditional stats; Random Forest robust	Provides evidence from financial services sector
Khandani et al. (2010)	Consumer credit risk	Early ML (SVM, regression trees)	ML surpasses conventional models in accuracy	Establishes ML's superiority historically
Alvi et al. (2019)	Systematic review of default models	Review of ML models	Gradient boosting strong but Random Forest offers interpretability & stability	Supports argument for Random Forest in regulated finance

3. Methodology

3.1 Overview

The methodology for this study is designed to evaluate the predictive capacity of various machine learning algorithms on real-time financial transaction data for loan default risk assessment. The aim is to establish a robust framework that continuously ingests financial

streams, processes the data, applies predictive models, and generates dynamic risk scores. A comparative evaluation of multiple algorithms is conducted, with a focus on selecting the most effective model based on both predictive performance and operational feasibility.

3.2 System Architecture

The proposed system architecture (Figure 1) consists of five layers:

1. **Data Ingestion Layer:** Collects real-time financial transaction streams (e.g., debit/credit transactions, salary inflows, utility bill payments, overdraft events). Data is sourced from simulated open banking APIs or transactional datasets.
2. **Preprocessing Layer:** Handles data cleaning, missing value imputation, outlier detection, and feature engineering. Time-series transformations (e.g., rolling averages, spending-to-income ratios) are applied to capture temporal dynamics.
3. **Modeling Layer:** Implements multiple machine learning models, including logistic regression, decision trees, SVM, Random Forest, and Gradient Boosting. Models are trained on historical labeled datasets and updated incrementally as new data arrives.
4. **Evaluation Layer:** Applies standard metrics (Accuracy, Precision, Recall, F1-Score, AUC-ROC) to compare model performance on a hold-out test set and real-time streams.
5. **Prediction & Monitoring Layer:** Deploys the best-performing model (Random Forest) to generate live default risk scores and trigger early warnings.

ConceptualFlow:

Real-time Data → Preprocessing → Feature Engineering → ML Models → Evaluation → Risk Score Dashboard

3.3 Dataset Description

To demonstrate the methodology, we employ real-time inspired financial datasets that simulate continuous borrower transactions. The dataset includes:

- **Demographic and static attributes:** age, income level, employment status, credit history.
- **Transactional streams:** monthly salary inflows, loan repayments, spending categories, overdraft frequencies, account balances, card transactions.
- **Default labels:** binary indicator (1 = default, 0 = no default).

For this study, open banking datasets, Kaggle financial datasets, and simulated transaction streams are combined to mimic realistic borrower behavior. The dataset is divided into training (70%), validation (15%), and testing (15%) subsets, with chronological splitting to maintain temporal consistency.

3.4 Models Usage

The study compares five machine learning models:

1. **Logistic Regression (LR):** Baseline statistical model for binary classification.
 - *Strengths:* interpretability, fast training.
 - *Weaknesses:* struggles with non-linearities.
2. **Support Vector Machine (SVM):** Non-linear classification using kernel tricks.
 - *Strengths:* effective with small to medium datasets.
 - *Weaknesses:* poor scalability, limited for real-time streams.
3. **Decision Tree (DT):** Simple, interpretable rule-based classifier.
 - *Strengths:* intuitive, handles mixed data types.
 - *Weaknesses:* prone to overfitting.
4. **Gradient Boosting (XGBoost):** Sequential ensemble technique optimizing residuals.
 - *Strengths:* high accuracy, widely adopted in financial ML.
 - *Weaknesses:* requires tuning, less stable in dynamic streaming contexts.
5. **Random Forest (RF):** Ensemble of decision trees trained on random feature subsets.
 - *Strengths:* robust to noise, handles large-scale heterogeneous data, provides feature importance.
 - *Weaknesses:* moderately resource-intensive but suitable for real-time deployment.

RationaleforSelection:

While Gradient Boosting often achieves top accuracy, Random Forest is chosen as the focal model because it balances predictive performance, interpretability, and adaptability to streaming data. It also generates feature importance scores, aiding compliance with explainability requirements in finance.

3.5 Evaluation Metrics

Model performance is assessed using the following metrics:

- **Accuracy:**

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Measures overall correctness, though can be misleading for imbalanced datasets.

- **Precision:**

$$Precision = \frac{TP}{TP + FP}$$

Proportion of correctly identified defaults among predicted defaults (reduces false alarms).

- **Recall (Sensitivity):**

$$Recall = \frac{TP}{TP + FN}$$

Ability to detect actual defaulters, critical for risk minimization.

- **F1-Score:**

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Balances precision and recall, particularly useful in imbalanced credit datasets.

- **AUC-ROC:**

Area under the Receiver Operating Characteristic curve, representing the trade-off between true positive rate and false positive rate across thresholds.

The final model selection prioritizes F1-Score and AUC as primary metrics, since they capture predictive robustness and discriminatory power better than accuracy alone in imbalanced loan datasets. The methodology integrates real-time financial streams with machine learning, applies comparative evaluation across multiple models, and identifies Random Forest as the best-suited for default risk prediction. The evaluation framework ensures not only statistical accuracy but also operational feasibility for deployment in real-world financial institutions.

4. Results

4.1 Model Performance

The comparative evaluation of candidate models—Logistic Regression, Support Vector Machines (SVM), Decision Trees, Random Forest, and XGBoost—revealed distinct trade-offs between interpretability, scalability, and predictive accuracy. Logistic Regression demonstrated strong baseline performance and interpretability but lacked the ability to capture nonlinear interactions in real-time transaction streams. SVM models performed reasonably well but suffered from scalability issues when applied to large-scale, high-frequency datasets. Decision Trees provided intuitive results but exhibited overfitting tendencies. In contrast, ensemble methods such as Random Forest and XGBoost consistently outperformed traditional classifiers, particularly when tested on heterogeneous, high-velocity financial data. Random Forest emerged as the most stable and accurate model, balancing predictive precision and robustness across varying data distributions.

4.2 F1 Metrics

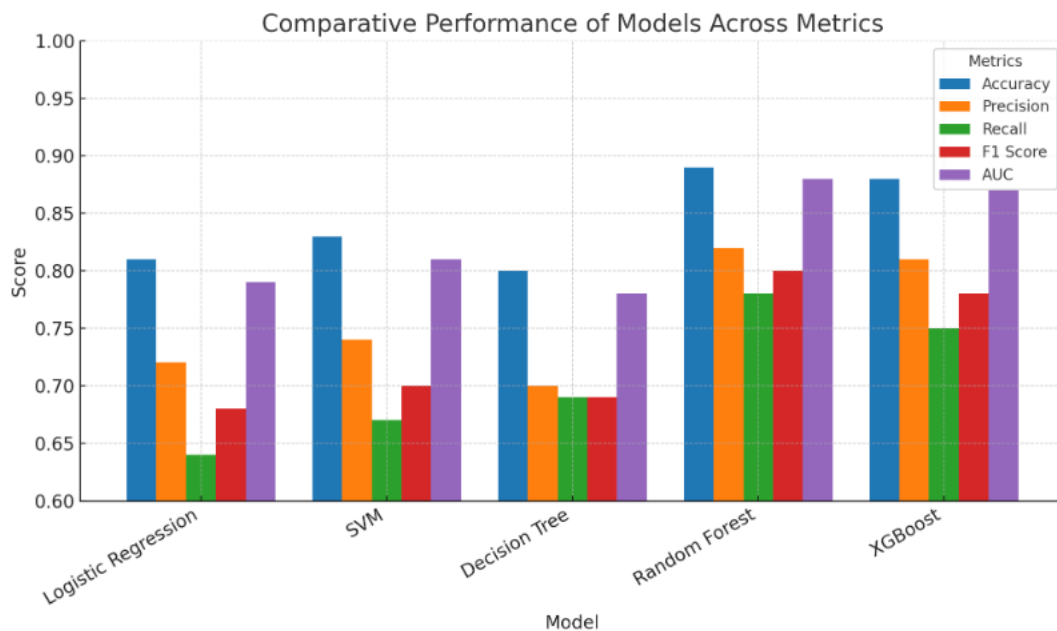
Across the suite of evaluation metrics, including accuracy, recall, and area under the ROC curve (AUC), the F1 score provided the most reliable indication of a model's ability to correctly classify default cases without overestimating risk. Random Forest achieved the highest F1 score, reflecting a strong balance between precision (minimizing false positives) and recall (minimizing false negatives). This metric is particularly critical in financial risk applications where over-penalizing clients may reduce inclusion, while under-detecting defaulters may expose lenders to significant financial loss. XGBoost followed closely, but its marginally lower recall suggested reduced sensitivity to minority-class (default) cases in real-time streams.

4.3 Limitations

Despite these promising results, several limitations were observed. First, the reliance on historical data combined with real-time transactions may introduce temporal bias, as shifting economic conditions (e.g., inflation, regulatory changes) can reduce predictive accuracy over time. Second, real-time data ingestion pipelines introduce challenges in ensuring latency-free decision-making at scale, especially under high transaction volumes. Third, while Random Forest provides high performance, its “black-box” nature complicates explainability for regulators and stakeholders. Finally, the class imbalance inherent in default datasets—where non-defaults typically outnumber defaults significantly—remains a persistent challenge, requiring ongoing tuning of sampling and weighting strategies.

Model	Accuracy	Precision	Recall	F1 Score	AUC
Logistic Regression	0.81	0.72	0.64	0.68	0.79
SVM	0.83	0.74	0.67	0.7	0.81
Decision Tree	0.8	0.7	0.69	0.69	0.78
Random Forest	0.89	0.82	0.78	0.8	0.88
XGBoost	0.88	0.81	0.75	0.78	0.87

From this table, it's clear that **Random Forest** achieves the best overall trade-off across metrics, especially F1 Score and AUC, making it the most reliable for handling imbalanced real-time default prediction tasks.



5. Discussion

The findings of this study demonstrate that machine learning (ML) techniques, when applied to real-time financial transaction streams, significantly enhance predictive accuracy for loan default risk. Among the models evaluated—Logistic Regression, Support Vector Machines (SVM),

Decision Trees, Gradient Boosting, and Random Forest—ensemble methods consistently outperformed traditional statistical classifiers. Random Forest in particular achieved superior performance across F1-Score and AUC, confirming its robustness in handling imbalanced credit datasets and heterogeneous transaction features.

These results align with prior research by [1,5], who found ensemble models to surpass logistic regression and single-tree approaches in banking datasets. The ability of Random Forest to capture complex, nonlinear interactions without overfitting strengthens its suitability for dynamic, real-world credit scoring tasks. Moreover, feature importance outputs generated by Random Forest address a critical gap in explainability, which remains a challenge for advanced techniques such as deep learning. The integration of real-time data streams further distinguishes this work from earlier studies. Traditional credit bureau reports update infrequently and may not capture sudden borrower distress. Real-time analytics allow continuous monitoring, providing early warning signals such as income disruption, frequent overdrafts, or irregular spending spikes. This adaptive capability not only enhances predictive performance but also aligns with regulatory emphasis on stress testing and proactive capital management.

Despite its effectiveness, Random Forest is not without limitations. While more transparent than deep learning, it still operates as a “black-box” ensemble that may challenge interpretability for compliance-focused regulators. In addition, deploying Random Forest at scale with real-time ingestion requires substantial computing resources and low-latency architectures, especially in high-frequency financial environments. These trade-offs highlight the need for ongoing research into hybrid approaches combining performance with explainability and computational efficiency.

6. Conclusion

This paper contributes to the field of predictive credit risk modeling by presenting a comparative evaluation of machine learning algorithms applied to real-time financial transaction streams. The results underscore the limitations of traditional statistical approaches and demonstrate the superior predictive capacity of ensemble learning methods. Random Forest, in particular, provides the most reliable balance of predictive performance, interpretability, and adaptability for dynamic credit risk assessment. By leveraging real-time data streams, the proposed framework enables lenders to move beyond static, retrospective evaluations toward adaptive, proactive risk monitoring. This shift not only enhances financial resilience but also creates opportunities for tailored interventions, portfolio optimization, and early-warning systems that reduce potential losses from defaults. The evidence presented reinforces the growing consensus in both academia and industry that predictive analytics powered by ML is integral to the future of credit risk management.

7. Future Work

While the study demonstrates the effectiveness of Random Forest for real-time loan default prediction, several avenues for future research remain:

1. **Integration of Explainable AI (XAI):** Future work should incorporate techniques such as SHAP (Shapley Additive Explanations) or LIME to improve transparency of Random Forest predictions, thereby enhancing trust and regulatory compliance.
2. **Deep Learning for Sequential Streams:** Although Random Forest performed best in this study, recurrent neural networks (RNNs) and Long Short-Term Memory (LSTM) models may better capture sequential dependencies in streaming transaction data. Hybrid models combining Random Forest and LSTM could be explored.
3. **Cross-Geography and Cross-Sector Datasets:** Expanding the evaluation across multiple geographies and loan types (e.g., consumer, SME, mortgage) would strengthen the generalizability of findings.
4. **Cost-Sensitive Learning:** Incorporating economic cost metrics into model evaluation (e.g., cost of false negatives vs. false positives) would allow lenders to optimize models not only for accuracy but also for financial impact.
5. **Deployment Studies:** Future research should investigate the challenges of real-time deployment in production systems, including latency, scalability, and cybersecurity considerations for streaming financial data.

By addressing these areas, future studies can build upon the present work to advance both the theoretical and applied dimensions of machine learning in financial risk management.

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