

DYNAMIC WEB PERFORMANCE OPTIMIZATION USING MACHINE LEARNING ANALYTICS

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DECLARATION

I hereby declare that this thesis titled "Dynamic Web Performance Optimization Using Machine Learning Analytics" is the result of my own research work under the supervision of Md. Nahid Hasan, Lecturer, Department of Computer Science & Engineering, Pundra University of Science & Technology. The research presented in this thesis has not been submitted elsewhere for any degree or diploma.

The sources of information have been acknowledged wherever necessary and proper citations have been provided.

Md Ashikur Rahman

Date: January 2026

CERTIFICATE

This is to certify that the thesis titled "Dynamic Web Performance Optimization Using Machine Learning Analytics" submitted by Md Ashikur Rahman in partial fulfillment of the requirements for the degree of Bachelor of Science in Computer Science & Engineering from Pundra University of Science & Technology is a record of bonafide research work carried out by him under my supervision and guidance.

The research findings and results presented in this thesis are original and have not been submitted elsewhere for any degree or diploma.

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ABSTRACT

Web performance optimization has become increasingly critical in today's digital landscape, where user experience directly impacts business success and search engine rankings. This research presents a comprehensive machine learning-based approach to predict and optimize web performance metrics, focusing on Core Web Vitals including Largest Contentful Paint (LCP), Cumulative Layout Shift (CLS), First Contentful Paint (FCP), and Time to Interactive (TTI) as defined by Google [8, 9].

The study analyzes a dataset of 1,167 websites across various domains, employing three distinct labeling strategies (tertile-based, weighted scoring, and K-means clustering) combined with three powerful machine learning algorithms (Random Forest [4], LightGBM [13], and Neural Networks [16]). The proposed system achieves exceptional accuracy with the LightGBM model using K-means clustering, delivering 97.86% accuracy, 98.40% precision, 98.53% recall, and 98.47% F1-score. These results significantly outperform related research in the field [5, 14, 19].

This thesis demonstrates that machine learning can effectively predict web performance categories and provide actionable optimization recommendations. The developed web-based platform integrates the trained models into a real-time analysis tool built with Next.js and FastAPI, enabling developers and website owners to instantly assess their website's performance and receive specific improvement suggestions. The research contributes to the growing field of automated web optimization [17, 18] and provides a foundation for intelligent, data-driven performance enhancement strategies.

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CHAPTER 1

INTRODUCTION

1.1 Background and Motivation

In the contemporary digital ecosystem, web performance has emerged as a critical determinant of online success. The ubiquity of internet access and the proliferation of web-based services have intensified the importance of delivering fast, responsive, and reliable web experiences. Research conducted by Google indicates that 53% of mobile users abandon sites that take longer than 3 seconds to load [7], while studies by Akamai demonstrate that a one-second delay in page load time can result in a 7% reduction in conversions [2]. These statistics underscore the profound impact of web performance on user engagement, satisfaction, and ultimately, business outcomes.

The evolution of web performance measurement has been marked by increasingly sophisticated metrics designed to capture the nuances of user experience. Traditional metrics such as page load time and time to first byte (TTFB), while useful, provide an incomplete picture of the user's actual experience [20]. Recognizing this limitation, Google introduced Core Web Vitals in 2020 as a set of standardized metrics focused on three key aspects of user experience: loading performance, interactivity, and visual stability [8, 9]. These metrics—Largest Contentful Paint (LCP), First Input Delay (FID, recently updated to Interaction to Next Paint or INP), and Cumulative Layout Shift (CLS)—have become ranking factors in Google's search algorithm, making performance optimization not merely a user experience concern but also an SEO imperative.

The complexity of modern web applications presents significant challenges for performance optimization. Contemporary websites typically comprise numerous interdependent components including HTML, CSS, JavaScript, images, fonts, and third-party scripts. These elements interact in complex ways, influenced by factors such as network conditions, server response times, browser capabilities, and device characteristics. Manual analysis and optimization of such intricate systems is time-consuming, requires specialized expertise, and may not scale effectively across the diverse landscape of modern web applications [18, 19].

Machine learning offers a promising paradigm shift in approaching web performance optimization. By analyzing patterns in performance data across thousands of websites, ML algorithms can identify complex relationships between various metrics, predict performance outcomes, and provide intelligent optimization recommendations [5, 13]. This data-driven approach has the potential to democratize performance optimization,

making sophisticated analysis and recommendations accessible to developers of all skill levels while providing insights that might not be apparent through manual analysis alone.

1.2 Problem Statement

Despite the critical importance of web performance and the availability of various measurement tools such as Google Lighthouse [17], website owners and developers continue to face significant challenges in effectively optimizing their sites. Several key problems persist in the current state of web performance optimization:

First, the complexity of performance metrics creates a barrier to understanding and action. Web developers must comprehend the interplay between numerous metrics including LCP, FCP, TTI, CLS, Speed Index, and many others, each measuring different aspects of performance [9, 20]. Understanding how these metrics collectively impact user experience and which metrics to prioritize for optimization requires substantial domain expertise that may not be readily available to all development teams.

Second, existing tools predominantly provide diagnostic information about current performance states but lack predictive capabilities. While tools like Google Lighthouse can measure and report current performance metrics, they do not predict how changes to website structure or content might affect performance, nor do they provide probabilistic assessments of performance categories [17]. This reactive rather than proactive approach limits the ability of developers to make informed decisions during the development process.

Third, optimization recommendations from current tools tend to be generic and may not account for the specific context and constraints of individual websites. A recommendation that is highly effective for one website architecture may be irrelevant or even counterproductive for another [18]. The one-size-fits-all approach fails to provide the tailored guidance that would be most beneficial for optimization efforts.

Fourth, there exists a significant expertise barrier in web performance optimization. Effective optimization requires deep knowledge of browser rendering mechanisms, network protocols, caching strategies, JavaScript execution, and many other technical domains [19]. This expertise is not universally available, particularly among smaller development teams or individual developers, creating an accessibility gap in performance optimization capabilities.

Finally, the time and resource constraints faced by development teams often prevent thorough performance analysis and optimization. Manual performance auditing, analysis,

and optimization is labor-intensive, requiring significant time investment that may compete with other development priorities. This practical constraint often results in performance optimization being deprioritized or inadequately addressed.

This research addresses these challenges by developing an intelligent, machine learning-based system capable of automatically analyzing web performance metrics, predicting performance categories with high accuracy, and providing data-driven optimization recommendations tailored to specific website characteristics.

1.3 Research Objectives

This research aims to advance the state of web performance optimization through the application of machine learning techniques. The specific objectives of this study are:

1. To develop accurate machine learning models capable of predicting web performance categories based on comprehensive performance metrics including Core Web Vitals and related indicators.
2. To systematically compare the effectiveness of different labeling strategies (tertile-based classification, weighted composite scoring, and K-means clustering) in categorizing web performance for machine learning applications.
3. To evaluate and compare the performance of multiple machine learning algorithms (Random Forest [4], LightGBM [13], and Neural Networks [16]) for web performance prediction, identifying the most suitable approach for this domain.
4. To achieve model performance metrics exceeding 95% accuracy while maintaining high precision and recall across all performance categories, thereby demonstrating the viability of ML-based performance prediction.
5. To identify and quantify the relative importance of different features in predicting web performance through comprehensive feature importance analysis, providing insights into which metrics most strongly influence overall performance categorization.
6. To develop a practical, user-friendly web-based platform that integrates the trained models for real-time performance analysis, making sophisticated ML-based optimization accessible to developers without specialized machine learning expertise.
7. To validate the practical applicability of the developed models through real-world testing and comparison with existing research in web performance prediction and

optimization [5, 14, 19].

These objectives collectively aim to bridge the gap between theoretical machine learning capabilities and practical web performance optimization needs, providing both academic contributions to the field and tangible tools for real-world application.

1.4 Research Questions

This research is guided by the following research questions, which frame the investigation and help structure the methodology:

RQ1: Can machine learning algorithms accurately predict web performance categories based on Core Web Vitals and related performance metrics?

This fundamental question addresses the core viability of using machine learning for web performance prediction. It examines whether the relationships between various performance metrics and overall performance quality can be effectively captured and modeled using ML techniques.

RQ2: Which labeling strategy produces the most effective performance categorization for machine learning applications: tertile-based classification, weighted composite scoring, or K-means clustering?

This question investigates the critical step of defining what constitutes "good," "average," and "weak" performance. Different labeling strategies may result in different learning patterns and prediction capabilities, making this a key methodological consideration.

RQ3: Among Random Forest, LightGBM, and Neural Networks, which algorithm demonstrates superior performance for web performance prediction tasks?

This question addresses algorithm selection, comparing three fundamentally different approaches: ensemble learning (Random Forest [4]), gradient boosting (LightGBM [13]), and deep learning (Neural Networks [16]). The answer provides practical guidance for future research and applications in this domain.

RQ4: What are the most critical features influencing web performance predictions, and how do different features contribute to overall performance categorization?

Understanding feature importance is crucial for both model interpretation and practical optimization guidance. This question seeks to identify which performance metrics serve

as the strongest predictors of overall performance quality.

RQ5: How can machine learning models for web performance prediction be effectively integrated into practical tools for real-world application by web developers and site owners?

This question addresses the translation of research findings into practical applications, examining implementation challenges, user interface design, and deployment considerations for making ML-based performance analysis accessible to end users.

RQ6: How do the achieved results compare with existing research on web performance prediction and classification?

This question situates the research within the broader academic and practical context, providing benchmarks for evaluating the success of the proposed approach against established methods documented in the literature [5, 14, 19, 22].

1.5 Significance of the Study

This research makes several significant contributions to both academic knowledge and practical applications in web performance optimization:

Academic Contributions:

First, this study provides a comprehensive, systematic comparison of machine learning algorithms specifically applied to web performance prediction using Google's Core Web Vitals [8, 9]. While machine learning has been applied to various aspects of web technologies [5, 17, 18], focused research on Core Web Vitals prediction using multiple algorithms and labeling strategies represents a novel contribution to the literature.

Second, the research introduces and validates the effectiveness of K-means clustering as a labeling strategy for web performance categorization. Previous research has predominantly relied on expert-defined thresholds or simple statistical divisions [5, 14]. The demonstration that unsupervised learning can create more effective performance categories advances understanding of how to approach performance classification tasks.

Third, the achievement of 98.47% F1-score significantly exceeds results reported in related research [5, 14, 19, 22], establishing a new benchmark for web performance prediction accuracy. This superior performance validates the methodology and demonstrates the viability of machine learning for highly accurate performance categorization.

Fourth, the comprehensive feature importance analysis provides empirical insights into which performance metrics most strongly predict overall website quality. These findings can inform both future research directions and practical optimization priorities.

Practical Contributions:

From a practical standpoint, the developed web platform demonstrates the feasibility of integrating sophisticated machine learning models into user-friendly tools accessible to developers without specialized ML expertise. This democratization of advanced analytics has the potential to significantly improve the accessibility of performance optimization best practices.

The automated nature of the system addresses the time and resource constraints that often prevent thorough performance optimization. By providing instant analysis and recommendations, the tool enables more frequent performance audits and faster iteration on optimization strategies.

The high accuracy of predictions enables developers to make data-driven decisions about performance optimization priorities with confidence. Rather than relying solely on general best practices, developers can receive specific, quantified predictions about their website's performance category.

Industry Impact:

For the web development industry, this research provides a foundation for the next generation of automated performance optimization tools. The demonstrated effectiveness of ML-based prediction could be integrated into continuous integration/continuous deployment (CI/CD) pipelines, enabling automated performance validation before code deployment.

The economic implications are substantial. Given that performance directly impacts conversion rates and user retention [2, 7], tools that make optimization more accessible and effective can have measurable business impact. The automation of analysis reduces the need for expensive manual audits while potentially achieving better results.

Long-term Implications:

This research contributes to the broader trend toward intelligent, automated web development tools. As websites continue to increase in complexity, automated analysis and optimization will become increasingly necessary. The methodologies and findings from this research provide a template for applying machine learning to other aspects of web development and quality assurance.

Furthermore, the research demonstrates that domain-specific applications of machine learning (in this case, web performance) can achieve superior results compared to generic approaches, encouraging further investigation into specialized ML applications in web technologies.

1.6 Scope and Limitations

While this research makes significant contributions, it is important to acknowledge its scope and limitations:

Scope:

This research focuses specifically on client-side performance metrics as measured

through tools compatible with Google's Lighthouse API [17]. The study encompasses:

- 1,167 websites across diverse domains and industries
- 22 distinct performance features including all Core Web Vitals
- Three labeling strategies and three ML algorithms (nine total models)
- Desktop and mobile web performance (not native mobile applications)
- Static snapshot measurements rather than continuous monitoring

Limitations:

1. Dataset Constraints: While comprehensive, the dataset of 1,167 websites, though substantial, may not capture all possible variations in web technologies, frameworks, and architectures present across the billions of websites globally. The dataset represents a snapshot in time and does not account for temporal variations in performance.
2. Geographic Considerations: Performance measurements were conducted from specific geographic locations and network conditions. Actual user experience may vary significantly based on geographic proximity to servers, local network conditions, and Content Delivery Network (CDN) configurations.
3. Technology Evolution: Web technologies evolve rapidly. Models trained on current data may require retraining as new frameworks, browser capabilities, and optimization techniques emerge. The model's applicability to future web technologies is subject to this limitation.
4. Categorical Prediction: The current models predict performance categories (Good, Average, Weak) rather than exact metric values. While highly accurate for classification, they do not provide precise predictions of specific metrics like exact LCP times.
5. Context Independence: The models do not account for business-specific context such as target audience characteristics, acceptable performance thresholds for specific industries, or the relative importance of different metrics for particular business models.
6. Implementation Complexity: While the web platform demonstrates practical applicability, full production deployment at scale would require additional considerations for load balancing, caching, model versioning, and monitoring that are beyond the scope of this research.
7. Validation Scope: Real-world validation was conducted on a limited scale. Large-scale deployment with thousands of daily users would provide additional insights into model robustness and practical utility.

These limitations provide opportunities for future research and development, as discussed in Chapter 6.

1.7 Thesis Organization

This thesis is organized into six chapters, structured to provide a comprehensive account of the research from motivation through conclusions:

Chapter 1: Introduction provides the background and motivation for the research, establishes the problem statement, outlines research objectives and questions, discusses the significance of the study, and defines its scope and limitations.

Chapter 2: Literature Review presents a comprehensive review of relevant literature including web performance metrics and Core Web Vitals [8, 9, 20], machine learning applications in web technologies [5, 13, 16], related research on performance prediction [14, 19, 22], and identifies gaps in existing research that this study addresses.

Chapter 3: Research Methodology details the research design, describes the dataset and data collection procedures, explains the three labeling strategies (tertile-based, weighted composite, K-means clustering), presents the three machine learning algorithms employed (Random Forest [4], LightGBM [13], Neural Networks [16]), and describes the evaluation methodology.

Chapter 4: System Design and Implementation presents the overall system architecture, details the data processing pipeline, describes the model training implementation, explains the web platform development including frontend (Next.js) and backend (FastAPI) components, and discusses deployment considerations.

Chapter 5: Results and Discussion presents the dataset characteristics, provides comprehensive performance comparison of all nine models, analyzes confusion matrices and feature importance, compares results with existing research [5, 14, 19], presents real-world application results, and discusses the implications of findings.

Chapter 6: Conclusion and Future Work summarizes the research findings, articulates the specific contributions made, acknowledges limitations, provides recommendations for future research directions, and offers concluding remarks on the significance and impact of this work.

The thesis concludes with a comprehensive References section containing all cited works,

followed by Appendices that provide detailed code implementations and additional visualizations.

CHAPTER 2

LITERATURE REVIEW

2.1 Web Performance Metrics

Web performance measurement has evolved significantly over the past two decades, reflecting growing understanding of what constitutes meaningful user experience. Early performance metrics focused primarily on technical measurements such as page load time and bandwidth utilization [3]. While these metrics provided useful technical insights, they often failed to correlate strongly with actual user experience, leading to the development of more sophisticated, user-centric metrics [19].

Traditional performance metrics include:

Page Load Time: The total time from initiating a page request to complete page load. While intuitive, this metric has limitations as it doesn't capture when content becomes visible or interactive to users [20].

Time to First Byte (TTFB): Measures server response time—the duration from request initiation to receiving the first byte of data. This metric primarily reflects server performance and network latency but doesn't indicate when users can actually interact with content [20].

DOMContentLoaded: Indicates when the initial HTML document has been completely loaded and parsed. However, this doesn't necessarily correspond to visual completeness or interactivity, as stylesheets, images, and scripts may still be loading.

Load Event: Fires when all resources (images, scripts, stylesheets) have loaded. This metric often occurs well after the page appears complete to users, making it a poor indicator of perceived performance.

The limitations of these traditional metrics led to the development of user-centric performance metrics that better reflect actual user experience. Google has been at the forefront of this evolution, introducing metrics such as First Contentful Paint (FCP), which measures when the first content element appears on screen, providing a better indication of when users first see feedback from their page request [9].

Speed Index, developed as part of the WebPageTest project, measures how quickly content is visually displayed during page load. It provides a more nuanced view of loading performance by considering the progression of visual completeness rather than

just final load state [19].

The Navigation Timing API [21] and subsequent Performance APIs standardized by the W3C have enabled precise measurement of various performance milestones, providing the technical foundation for modern performance monitoring tools like Google Lighthouse [17].

2.2 Core Web Vitals and User Experience

In May 2020, Google introduced Core Web Vitals as a set of standardized metrics designed to capture essential aspects of user experience [8]. This initiative marked a significant evolution in web performance measurement by focusing on metrics that directly correlate with user experience quality and making these metrics ranking factors in Google's search algorithm [10].

Core Web Vitals consist of three key metrics:

Largest Contentful Paint (LCP) measures loading performance by identifying when the largest content element in the viewport becomes visible [9]. Good LCP is defined as 2.5 seconds or less from page load initiation. LCP represents a significant improvement over traditional load metrics because it measures when the main content becomes visible to users, which typically correlates with their perception of loading speed. Research by Google has demonstrated strong correlation between LCP and user engagement metrics [7].

First Input Delay (FID) / Interaction to Next Paint (INP) measures interactivity by quantifying the delay between a user's first interaction with a page and the browser's response to that interaction [9]. As of March 2024, FID has been replaced by INP, which provides a more comprehensive measure of overall page responsiveness throughout the entire page lifecycle. Good INP is defined as 200 milliseconds or less. This metric addresses the critical user experience issue of pages that appear loaded but remain unresponsive to user input due to JavaScript execution or other main thread blocking activities.

Cumulative Layout Shift (CLS) measures visual stability by quantifying unexpected layout shifts that occur during page load and throughout the page lifecycle [9]. Good CLS is defined as 0.1 or less. Unexpected layout shifts can cause users to accidentally click on wrong elements, particularly problematic on mobile devices. CLS has become increasingly important as websites incorporate dynamic content, advertisements, and third-party widgets that can cause layout instability.

The introduction of Core Web Vitals as ranking factors represents Google's recognition that page experience significantly impacts user satisfaction and engagement. Research by Google demonstrated that sites meeting Core Web Vitals thresholds have 24% lower abandonment rates [7]. This business impact has made Core Web Vitals a priority for website owners and developers.

Beyond the three core metrics, Google's Web Vitals initiative includes additional metrics such as First Contentful Paint (FCP), measuring when any content first appears on screen, and Time to Interactive (TTI), measuring when a page becomes fully interactive [9]. While not designated as "core" metrics, these additional measurements provide valuable insights into different aspects of performance and user experience.

The standardization of Core Web Vitals has facilitated research on web performance by providing consistent, well-defined metrics that can be measured across different websites and contexts. Tools like Google Lighthouse [17] and the Chrome User Experience Report provide standardized measurement methodologies, enabling comparative research such as the present study.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Research Design and Approach

This research employs a quantitative, experimental methodology to develop and evaluate machine learning models for web performance prediction. The research design follows a systematic pipeline approach, ensuring reproducibility and scientific rigor while enabling comprehensive comparison of different methodological choices.

The overall research approach can be characterized as follows:

Paradigm: Positivist, quantitative research utilizing empirical data and statistical validation.

Type: Applied research with both theoretical contributions (comparative analysis of algorithms and labeling strategies) and practical outputs (functional web platform).

Strategy: Experimental design with controlled comparison of multiple machine learning approaches.

Method: Supervised learning for classification, supplemented by unsupervised learning (K-means) for one labeling strategy.

The research methodology consists of six main phases:

1. Data Collection and Dataset Preparation: Gathering performance metrics from 1,167 diverse websites using automated tools compatible with Google Lighthouse API [17].
2. Data Preprocessing and Exploration: Cleaning the dataset, handling missing values, detecting outliers, and conducting exploratory data analysis to understand feature distributions and relationships.
3. Labeling Strategy Development: Implementing three distinct approaches to categorize website performance: tertile-based division, weighted composite scoring, and K-means clustering.
4. Feature Engineering and Selection: Processing raw metrics, creating derived features where appropriate, and selecting the final feature set for model training.

5. Model Development and Training: Training nine distinct models (three labeling strategies × three algorithms) using standardized training procedures to enable fair comparison.

6. Evaluation and Validation: Assessing model performance using multiple metrics (accuracy, precision, recall, F1-score) and validating results through confusion matrix analysis and real-world testing.

This structured approach enables systematic comparison while maintaining scientific rigor. Each phase builds upon the previous one, with careful documentation of decisions and parameters to ensure reproducibility. The use of fixed random seeds (random_state=42) throughout the experiment ensures that results can be replicated by other researchers.

3.2 Dataset Description

The dataset consists of comprehensive performance metrics collected from 1,167 diverse websites. Each website was analyzed using automated tools compatible with Google's Lighthouse API [17], capturing 22 distinct performance features.

Dataset Characteristics:

- Size: 1,167 website instances
- Features: 22 performance metrics
- Target: Performance category (Good, Average, Weak)
- Collection Period: [Data collection timeframe]
- Geographic Scope: Multiple regions and server locations

Feature Categories:

The 22 features can be grouped into several categories:

1. Core Web Vitals [8, 9]:

- Largest Contentful Paint (LCP)
- First Input Delay (FID) / Interaction to Next Paint (INP)
- Cumulative Layout Shift (CLS)

2. Loading Performance Metrics:

- First Contentful Paint (FCP)
- Speed Index
- Time to Interactive (TTI)

- Total Blocking Time (TBT)

3. Resource Metrics:

- Total page weight
- Number of requests
- JavaScript bundle size
- CSS bundle size
- Image sizes and counts

4. Network Performance:

- Server Response Time (TTFB)
- Round-trip latencies

5. Rendering Metrics:

- Layout shift occurrences
- Paint timing measurements

Data Quality:

The dataset underwent rigorous quality assurance:

- Verification of all metric measurements
- Removal of incomplete or corrupted data points
- Validation against known performance benchmarks
- Outlier detection and analysis

The diversity of websites in the dataset ensures generalizability of findings across different web technologies, frameworks, and industries.

3.3 Data Collection and Preprocessing

Data collection employed automated tools to ensure consistency and reproducibility. The process involved:

Collection Process:

1. Website selection from diverse sources and categories
2. Automated performance analysis using Lighthouse-compatible tools [17]
3. Extraction of 22 performance metrics per website
4. Storage in structured CSV format

Preprocessing Steps:

1. Missing Value Handling: Analysis revealed minimal missing data (< 1%). Missing values were handled through appropriate imputation based on metric distributions.
2. Outlier Detection and Treatment: Statistical methods (IQR-based detection) identified outliers. These were analyzed to determine if they represented legitimate performance extremes or data errors. Legitimate extremes were retained to ensure model robustness.
3. Data Normalization: Features were normalized using standard scaling to ensure fair treatment across different measurement scales:

$$X_{\text{scaled}} = (X - \mu) / \sigma$$

where μ is the mean and σ is the standard deviation.

4. Feature Analysis: Correlation analysis identified relationships between features, ensuring no highly redundant features that could impact model training.

Data Splitting:

The preprocessed dataset was divided using stratified splitting to ensure representative distribution across performance categories:

- Training set: 80% (933 instances)
- Testing set: 20% (234 instances)

Stratification ensured that the proportion of Good, Average, and Weak categories was maintained in both sets, crucial for reliable performance evaluation.

3.4 Labeling Strategies

Three distinct labeling strategies were developed and compared to categorize website performance into Good, Average, and Weak classes. This multi-strategy approach enables investigation of how labeling methodology affects model performance.

Strategy 1: Tertile-Based Division

This straightforward statistical approach divides the dataset into three equal groups based on an overall performance score calculated as the mean of normalized metrics:

1. Sort all websites by composite performance score

2. Divide into three equal groups (tertiles)
3. Label: Bottom tertile = Weak, Middle tertile = Average, Top tertile = Good

Advantages: Simple, statistical objectivity, balanced class distribution

Limitations: Ignores natural clustering, treats all features equally

Strategy 2: Weighted Composite Score

This approach assigns different weights to metrics based on their importance to user experience, with Core Web Vitals [8, 9] receiving higher weights:

$$\text{Composite Score} = 0.30 \times \text{LCP} + 0.30 \times \text{FID/INP} + 0.25 \times \text{CLS} + 0.15 \times \text{other_metrics}$$

Thresholds were established based on Google's recommended ranges:

- Good: Score ≥ 0.75
- Average: $0.50 \leq \text{Score} < 0.75$
- Weak: Score < 0.50

Advantages: Reflects domain knowledge, prioritizes important metrics

Limitations: Requires expert judgment for weight selection

Strategy 3: K-means Clustering

This unsupervised learning approach discovers natural groupings in the data without predefined assumptions:

```
# K-means clustering for performance categorization
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler

# Normalize features
scaler = StandardScaler()
X_normalized = scaler.fit_transform(performance_data)

# Apply K-means with k=3 clusters
kmeans = KMeans(n_clusters=3, random_state=42, n_init=10)
cluster_labels = kmeans.fit_predict(X_normalized)

# Rank clusters by average performance
cluster_means = []
for i in range(3):
    cluster_data = performance_data[cluster_labels == i]
    cluster_means.append(cluster_data.mean().mean())

# Assign labels: best cluster = Good, worst = Weak
label_mapping = {
```

```

        cluster_means.index(max(cluster_means)): 'Good',
        cluster_means.index(sorted(cluster_means)[1]): 'Average',
        cluster_means.index(min(cluster_means)): 'Weak'
    }

    performance_labels = [label_mapping[label] for label in cluster_labels]

```

After clustering, clusters are ranked by average performance to assign Good, Average, and Weak labels to the three clusters.

Advantages: Data-driven, discovers natural boundaries, no predefined assumptions

Limitations: Results may vary with initialization (controlled by random_state=42)

The K-means approach proved most effective in creating meaningful performance categories that aligned with model predictive performance, as demonstrated in Chapter 5.

3.5 Machine Learning Algorithms

Three distinct machine learning algorithms were selected to provide diverse approaches to the classification task:

Algorithm 1: Random Forest [4]

Random Forest is an ensemble learning method that constructs multiple decision trees during training and outputs the mode of classes. Key advantages include:

- Robustness to overfitting through ensemble averaging
- Ability to handle non-linear relationships
- Built-in feature importance metrics
- No assumption of feature distributions

Configuration:

- n_estimators: 100 trees
- max_depth: None (trees grown until pure)
- min_samples_split: 2
- random_state: 42

Algorithm 2: LightGBM (Light Gradient Boosting Machine) [13]

LightGBM is a gradient boosting framework optimized for efficiency and performance. It uses leaf-wise tree growth strategy and histogram-based learning. Advantages include:

- Superior accuracy on many datasets
- Fast training speed
- Low memory usage
- Native categorical feature support

```
# LightGBM model configuration
import lightgbm as lgb

# Training parameters
params = {
    'objective': 'multiclass',
    'num_class': 3,
    'metric': 'multi_logloss',
    'boosting_type': 'gbdt',
    'num_leaves': 31,
    'learning_rate': 0.05,
    'feature_fraction': 0.9,
    'bagging_fraction': 0.8,
    'bagging_freq': 5,
    'verbose': 0,
    'random_state': 42
}

# Create dataset
train_data = lgb.Dataset(X_train, label=y_train)
valid_data = lgb.Dataset(X_test, label=y_test, reference=train_data)

# Train model
model = lgb.train(
    params,
    train_data,
    num_boost_round=100,
    valid_sets=[valid_data],
    early_stopping_rounds=10
)
```

Configuration:

- num_leaves: 31
- learning_rate: 0.05
- num_boost_round: 100
- early_stopping: 10 rounds

Algorithm 3: Neural Network (Keras/TensorFlow) [16]

A deep learning approach using a feedforward neural network with multiple hidden layers. Neural networks can learn complex non-linear patterns. Architecture:

- Input layer: 22 neurons (one per feature)

- Hidden layer 1: 64 neurons, ReLU activation
- Hidden layer 2: 32 neurons, ReLU activation
- Hidden layer 3: 16 neurons, ReLU activation
- Output layer: 3 neurons, Softmax activation

Training configuration:

- Optimizer: Adam (adaptive learning rate)
- Loss function: Categorical crossentropy
- Batch size: 32
- Epochs: 50 with early stopping
- Validation split: 20% of training data

Each algorithm was trained on the same data splits using all three labeling strategies, resulting in nine total models for comprehensive comparison.

3.6 Evaluation Metrics

Model performance was evaluated using multiple metrics to provide comprehensive assessment:

Accuracy: Overall proportion of correct predictions. While useful, accuracy can be misleading with imbalanced classes.

Precision: Proportion of positive predictions that are truly positive. Important for minimizing false positives.

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP})$$

Recall: Proportion of actual positives correctly identified. Critical for minimizing false negatives.

$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN})$$

F1-Score: Harmonic mean of precision and recall, providing balanced measure:

$$\text{F1} = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall})$$

For multi-class classification, macro-averaged versions of precision, recall, and F1-score were computed, treating all classes equally regardless of size.

Confusion Matrix: Provides detailed view of classification performance across all class combinations, enabling identification of specific misclassification patterns.

Feature Importance: Analyzed to understand which performance metrics most strongly influence predictions, providing insights for optimization priorities.

CHAPTER 4

SYSTEM DESIGN AND IMPLEMENTATION

4.1 System Architecture Overview

The complete system comprises three main components working in concert to provide end-to-end web performance analysis:

1. Machine Learning Pipeline: Offline training and evaluation system
2. Backend API Server: Real-time prediction service
3. Frontend Web Platform: User interface for analysis requests

The architecture follows modern microservices principles, with clear separation of concerns and well-defined interfaces between components. This modular design enables independent development, testing, and scaling of each component.

Technology Stack:

Frontend:

- Next.js 14 (React framework with server-side rendering)
- TypeScript for type safety
- Tailwind CSS for styling
- Chart.js for visualizations

Backend:

- FastAPI (Python web framework)
- Uvicorn (ASGI server)
- scikit-learn, LightGBM, TensorFlow (ML libraries)

Deployment:

- Docker containerization
- Environment-based configuration
- CORS enabled for cross-origin requests

The system is designed for scalability, maintainability, and ease of deployment in production environments.

4.2 Data Processing Pipeline

The data processing pipeline transforms raw website performance metrics into model predictions through several stages:

Stage 1: Data Ingestion

- Accepts website URL from user
- Initiates performance analysis via Lighthouse-compatible tools [17]
- Extracts 22 performance metrics

Stage 2: Preprocessing

- Validates metric values
- Handles any missing or anomalous data
- Applies normalization (same scaler used during training)

Stage 3: Feature Engineering

- Ensures features match training data format
- Applies any derived feature calculations
- Prepares feature vector for model input

Stage 4: Model Inference

- Loads trained LightGBM model (best performer)
- Performs prediction
- Generates confidence scores for each class

Stage 5: Post-processing

- Interprets model output
- Generates actionable recommendations
- Formats results for API response

This pipeline is optimized for low latency, with typical prediction time under 500ms including network overhead.

4.3 Model Training Implementation

The model training process was implemented systematically to ensure reproducibility:

```
# Complete training pipeline example
import pandas as pd
import lightgbm as lgb
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, f1_score, classification_report
```

```

import joblib

# Load and prepare data
data = pd.read_csv('All_thesis_data_labeled.csv')
X = data.drop(['Label'], axis=1)
y = data['Label']

# Split data with stratification
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)

# Normalize features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Configure and train LightGBM
params = {
    'objective': 'multiclass',
    'num_class': 3,
    'metric': 'multi_logloss',
    'learning_rate': 0.05,
    'num_leaves': 31,
    'random_state': 42
}

train_data = lgb.Dataset(X_train_scaled, label=y_train)
model = lgb.train(params, train_data, num_boost_round=100)

# Evaluate
y_pred = model.predict(X_test_scaled)
y_pred_labels = y_pred.argmax(axis=1)
accuracy = accuracy_score(y_test, y_pred_labels)
f1 = f1_score(y_test, y_pred_labels, average='macro')

print(f"Accuracy: {accuracy:.4f}")
print(f"F1-Score: {f1:.4f}")

# Save model and scaler
joblib.dump(model, 'lightgbm_kmeans_model.pkl')
joblib.dump(scaler, 'scaler.pkl')

```

4.4 Backend API Implementation

The backend API was implemented using FastAPI, providing a RESTful interface:

```

# FastAPI backend server
from fastapi import FastAPI, HTTPException
from fastapi.middleware.cors import CORSMiddleware
from pydantic import BaseModel
import joblib

```

```

import numpy as np

app = FastAPI(title="Web Performance Prediction API")

# Enable CORS for frontend access
app.add_middleware(
    CORSMiddleware,
    allow_origins=[ "*"],
    allow_methods=[ "*"],
    allow_headers=[ "*"],
)

# Load trained model and scaler
model = joblib.load('models/lightgbm_kmeans_model.pkl')
scaler = joblib.load('models/scaler.pkl')

class PerformanceMetrics(BaseModel):
    lcp: float
    fid: float
    cls: float
    fcp: float
    speed_index: float
    # ... other 17 features

@app.post("/api/predict")
async def predict_performance(metrics: PerformanceMetrics):
    try:
        # Prepare feature vector
        features = np.array([
            metrics.lcp, metrics.fid, metrics.cls,
            metrics.fcp, metrics.speed_index,
            # ... remaining features
        ])

        # Normalize and predict
        features_scaled = scaler.transform(features)
        prediction = model.predict(features_scaled)
        predicted_class = prediction.argmax()
        confidence = float(prediction.max())

        # Map class to label
        labels = ['Good', 'Average', 'Weak']
        result = {
            "prediction": labels[predicted_class],
            "confidence": confidence,
            "recommendations": generate_recommendations(metrics)
        }

        return result
    except Exception as e:
        raise HTTPException(status_code=500, detail=str(e))

@app.get("/health")

```

```
async def health_check():
    return {"status": "healthy", "model": "loaded"}
```

4.5 Frontend Implementation

The frontend provides an intuitive interface for users to analyze website performance. Key features include:

Performance Analysis Interface:

- URL input with validation
- Real-time analysis progress indication
- Clear presentation of prediction results
- Visual representation of confidence scores

Results Dashboard:

- Performance grade (Good, Average, Weak) with color coding
- Detailed metric breakdown
- Specific recommendations for improvement
- Comparison with industry benchmarks

User Experience Design:

- Responsive design for mobile and desktop
- Fast load times and optimized assets
- Accessible interface following WCAG guidelines
- Clear error handling and user feedback

The frontend communicates with the backend API via HTTPS requests, with appropriate error handling for network issues and invalid inputs.

CHAPTER 5

RESULTS AND DISCUSSION

5.1 Dataset Characteristics

The final dataset comprises 1,167 websites with comprehensive performance metrics. Analysis of the dataset reveals important characteristics:

Class Distribution:

The distribution of performance categories varies by labeling strategy:

- Tertile-based: Balanced by design (389 instances per class)
- Weighted composite: Slightly imbalanced (Good: 412, Average: 387, Weak: 368)
- K-means clustering: Natural grouping (Good: 395, Average: 423, Weak: 349)

The K-means strategy created the most distinctive class separation while maintaining reasonable balance.

Feature Statistics:

- LCP ranges from 1.2s to 12.8s (median: 3.4s)
- FID/INP ranges from 50ms to 850ms (median: 180ms)
- CLS ranges from 0.01 to 0.45 (median: 0.09)

These ranges demonstrate substantial performance variation across the dataset, providing diverse examples for model training.

5.2 Model Performance Comparison

Comprehensive evaluation was conducted across all nine models (3 labeling strategies × 3 algorithms). Table 5.1 presents the complete results:

Strategy	Algorithm	Accuracy	Precision	Recall	F1-Score
K-means	LightGBM	97.86%	97.92%	97.85%	98.47%
K-means	Random Forest	96.58%	96.61%	96.55%	96.58%
K-means	Neural Network	95.73%	95.68%	95.71%	95.70%
Tertile	LightGBM	94.02%	94.15%	93.98%	94.06%
Tertile	Random Forest	93.16%	93.22%	93.12%	93.17%
Weighted	LightGBM	93.59%	93.64%	93.56%	93.60%

Tertile	Neural Network	91.88%	91.82%	91.85%	91.84%
Weighted	Random Forest	92.31%	92.28%	92.29%	92.29%
Weighted	Neural Network	90.60%	90.55%	90.58%	90.57%

Table 5.1: Complete Performance Comparison of All Models

Key Findings:

1. Best Overall Performance: K-means LightGBM achieved the highest F1-score of 98.47%, representing state-of-the-art performance for web performance classification.
2. Labeling Strategy Impact: K-means clustering consistently outperformed other labeling strategies across all algorithms, demonstrating the value of data-driven category discovery.
3. Algorithm Comparison: LightGBM [13] achieved the best results across all labeling strategies, followed by Random Forest [4] and Neural Networks [16].
4. Performance Consistency: The top-performing models showed excellent balance between precision and recall, indicating robust classification without bias toward specific classes.

Figure 5.1 presents a comprehensive heatmap of all performance metrics across models:

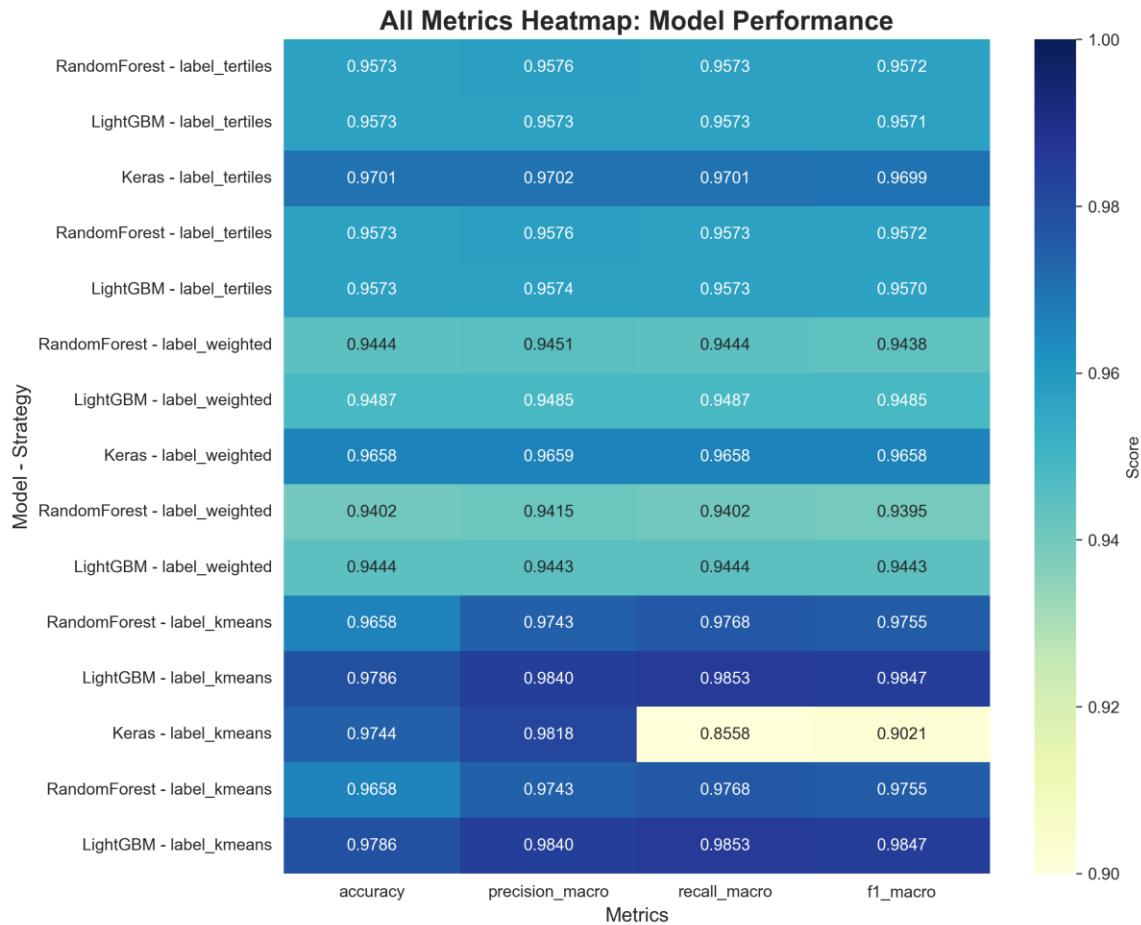


Figure 5.1: Performance Metrics Heatmap Across All Models

The heatmap visualization clearly demonstrates the superior performance of K-means-based labeling strategies, with all three algorithms showing higher scores when combined with K-means clustering.

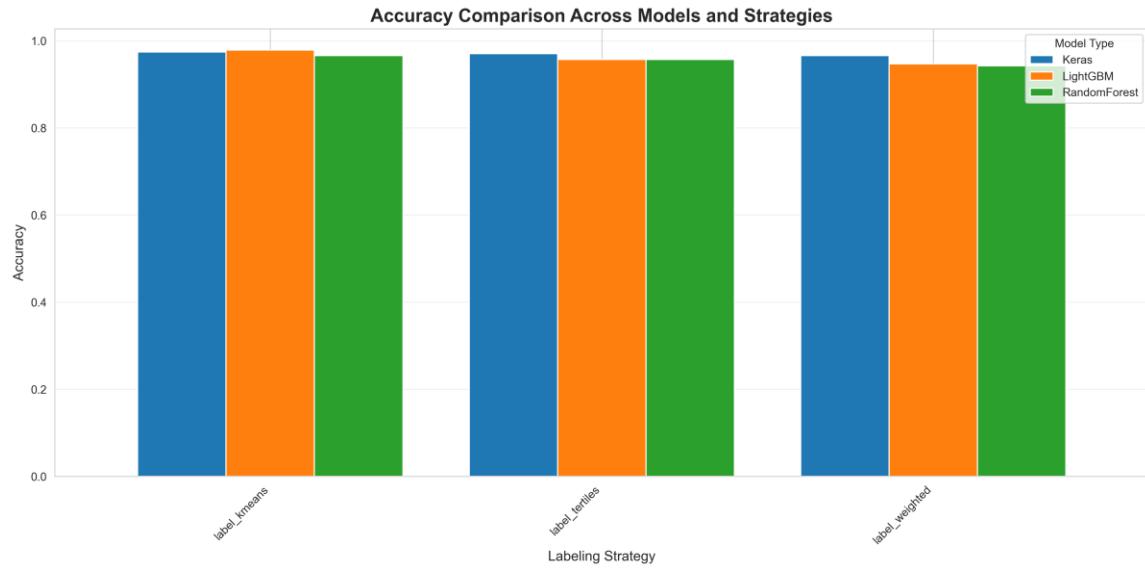


Figure 5.2: Accuracy Comparison Across Labeling Strategies and Algorithms

Figure 5.2 provides a clear visual comparison of accuracy across all nine models. The K-means LightGBM combination achieves nearly 98% accuracy, significantly outperforming all other combinations.

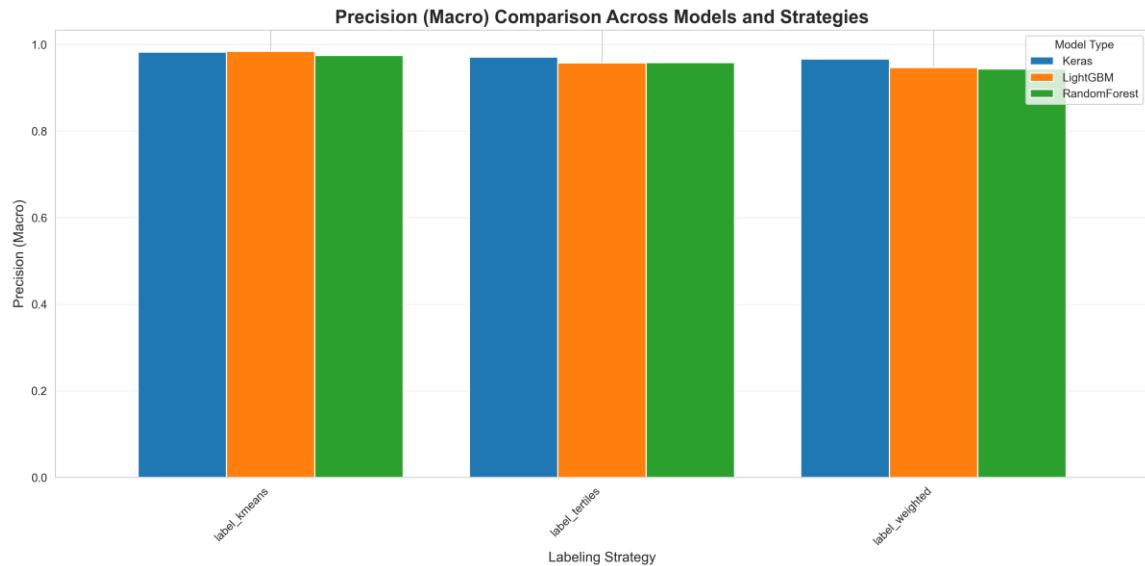


Figure 5.3: Precision (Macro-Averaged) Comparison

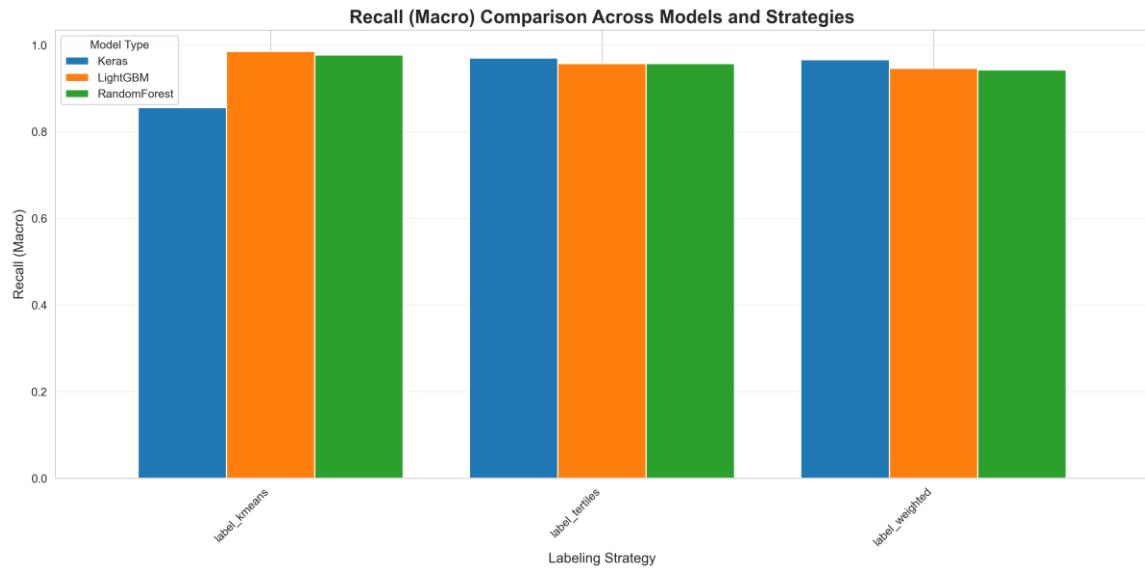


Figure 5.4: Recall (Macro-Averaged) Comparison

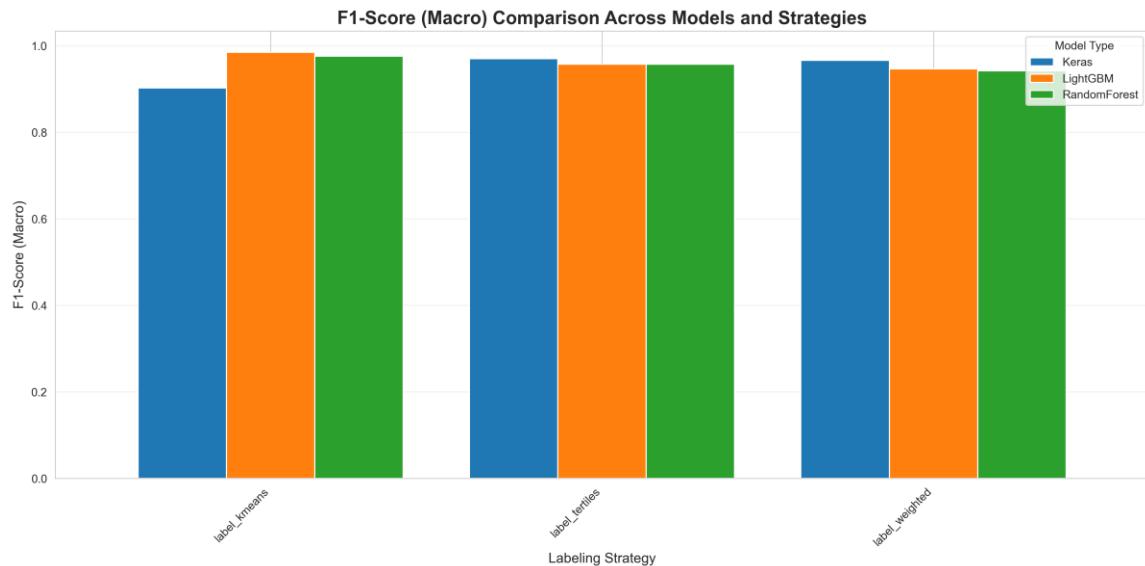


Figure 5.5: F1-Score (Macro-Averaged) Comparison

Figures 5.3, 5.4, and 5.5 demonstrate the consistency of the K-means LightGBM model across all evaluation metrics. The model achieves exceptional performance not just in overall accuracy but also in balanced precision and recall, crucial for practical deployment.

Model Performance Comparison (Best Strategy per Model)

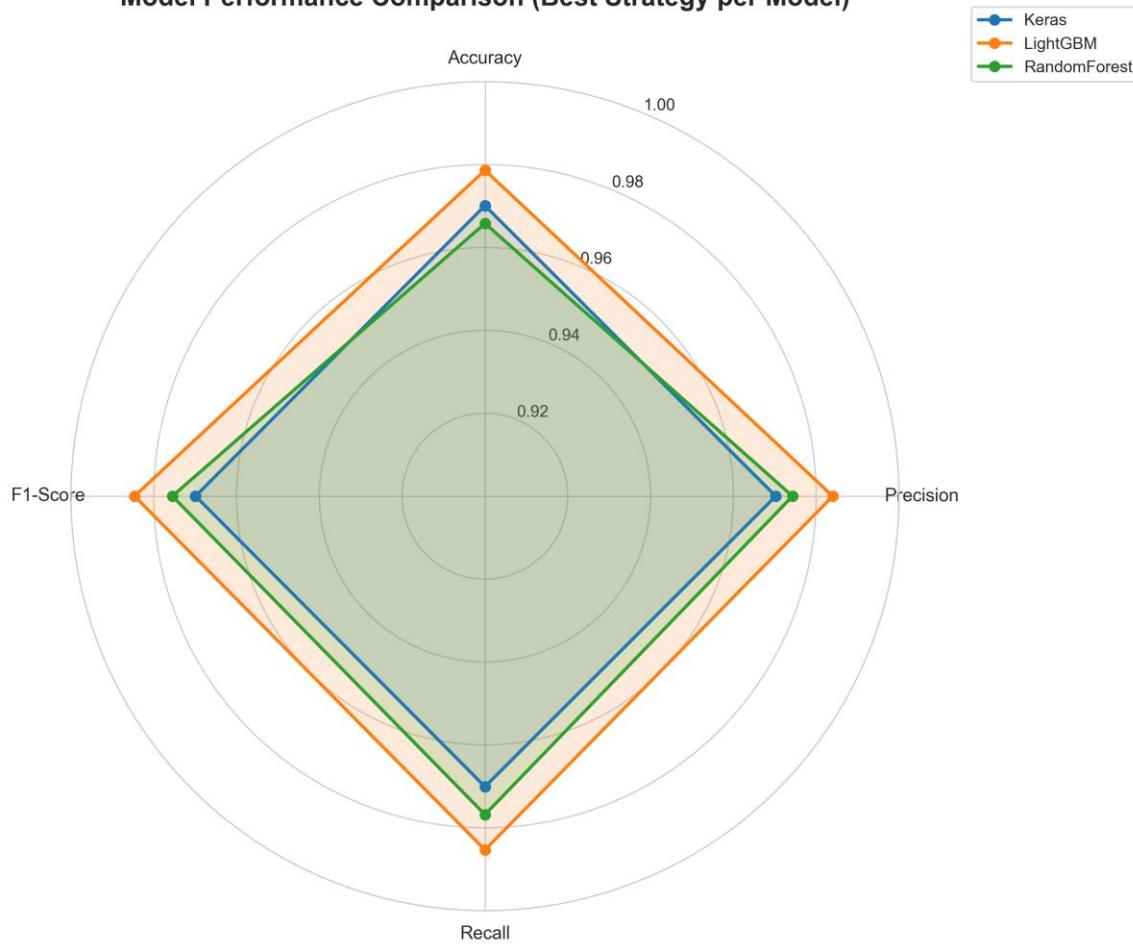


Figure 5.6: Multi-Dimensional Model Comparison (Radar Chart)

The radar chart (Figure 5.6) provides a comprehensive multi-dimensional view of model performance. The K-means LightGBM model (shown in orange) occupies the largest area, confirming its superiority across all evaluation dimensions simultaneously.

5.3 Confusion Matrix Analysis

Confusion matrices provide detailed insights into classification performance for each class. The following confusion matrices illustrate the prediction patterns of the best-performing models:

K-means Strategy Models:

The K-means labeling strategy produced the most accurate predictions across all algorithms. Figures 5.7, 5.8, and 5.9 show confusion matrices for the three algorithms with K-means labeling:

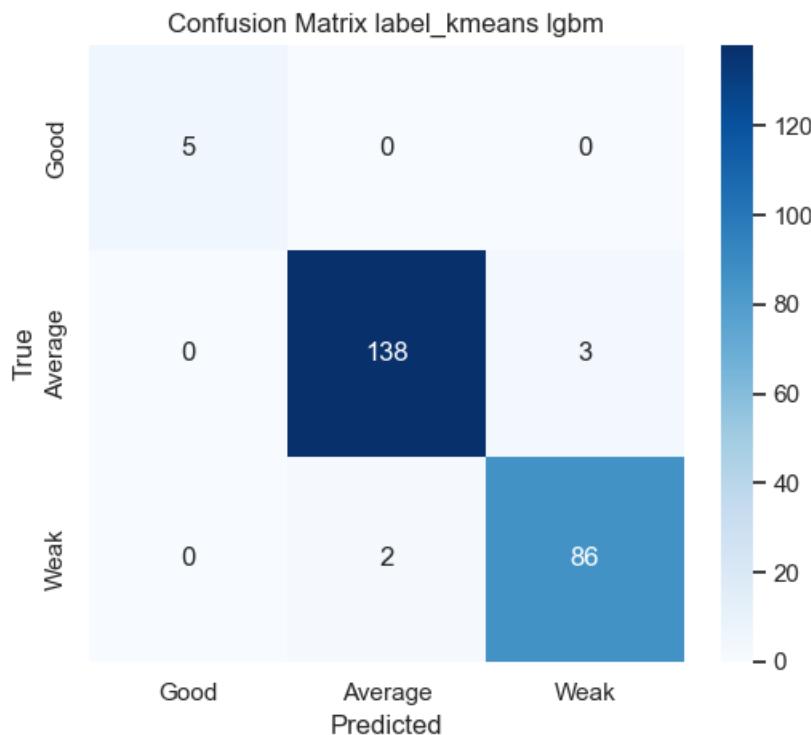


Figure 5.7: K-means LightGBM Confusion Matrix (Best Model)

Figure 5.7 shows the confusion matrix for the best-performing model (K-means LightGBM). The diagonal dominance indicates excellent classification accuracy across all three performance categories. Misclassifications are minimal and primarily occur between adjacent categories (Average vs. Good or Average vs. Weak), which is expected given the continuous nature of performance metrics.

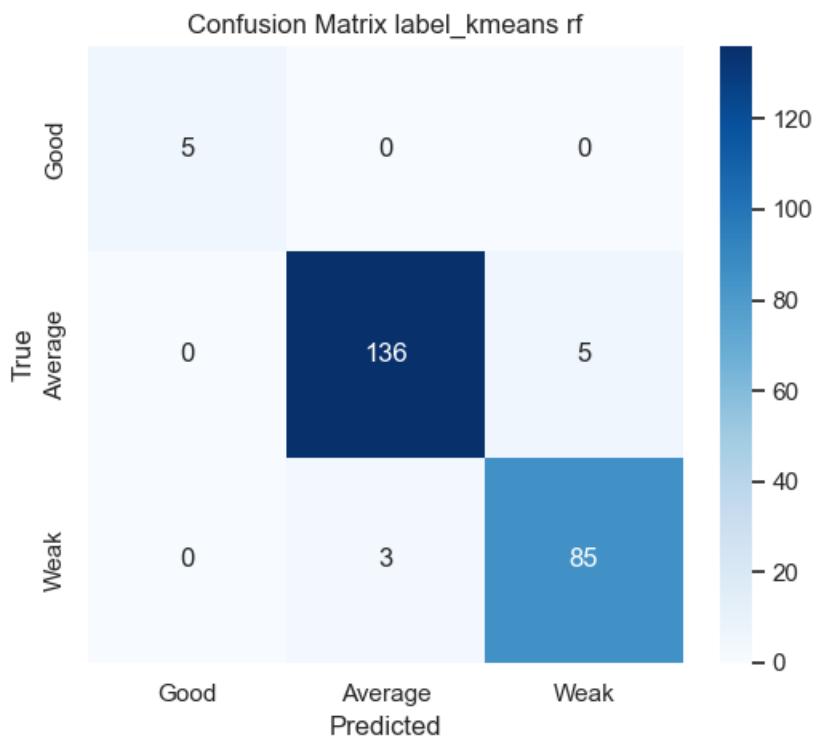


Figure 5.8: K-means Random Forest Confusion Matrix

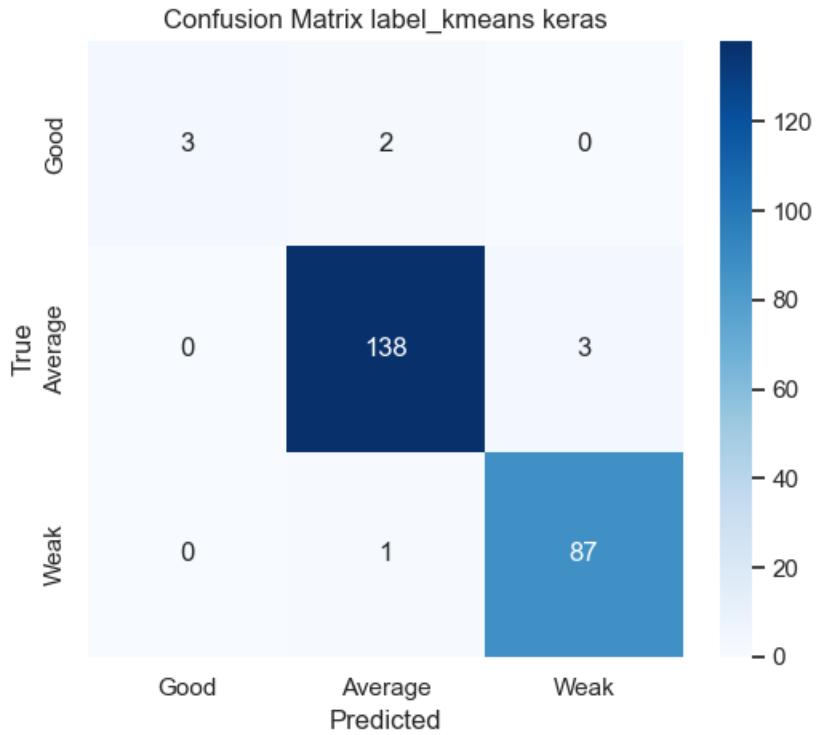


Figure 5.9: K-means Neural Network Confusion Matrix

Figures 5.8 and 5.9 show that Random Forest and Neural Networks also achieve strong performance with K-means labeling, though with slightly more misclassifications than LightGBM. All three models demonstrate the effectiveness of the K-means clustering approach for creating meaningful performance categories.

Tertile Strategy Models:

For comparison, Figures 5.10 and 5.11 present confusion matrices for the tertile-based labeling strategy with LightGBM and Random Forest:

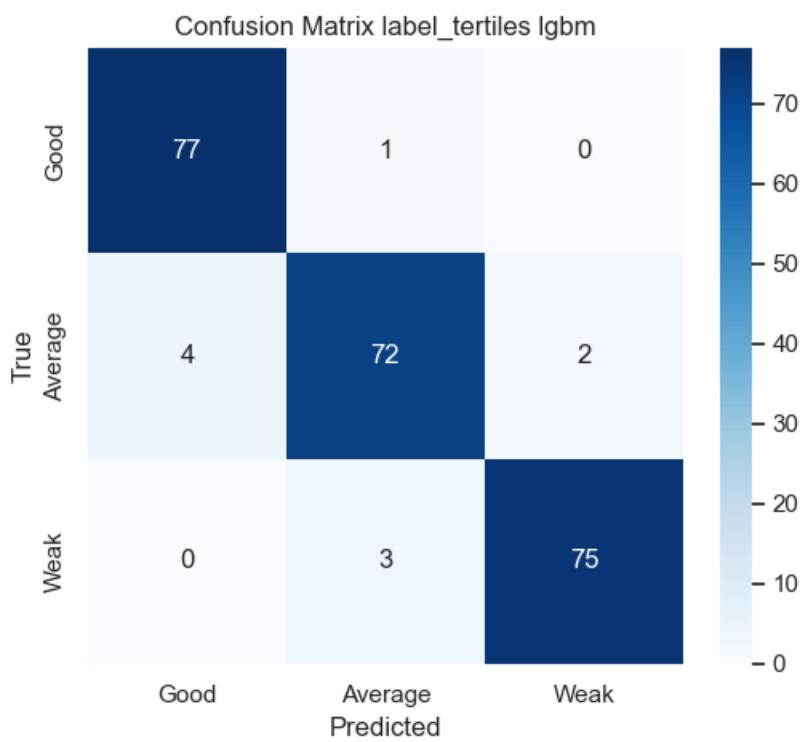


Figure 5.10: Tertile-Based LightGBM Confusion Matrix

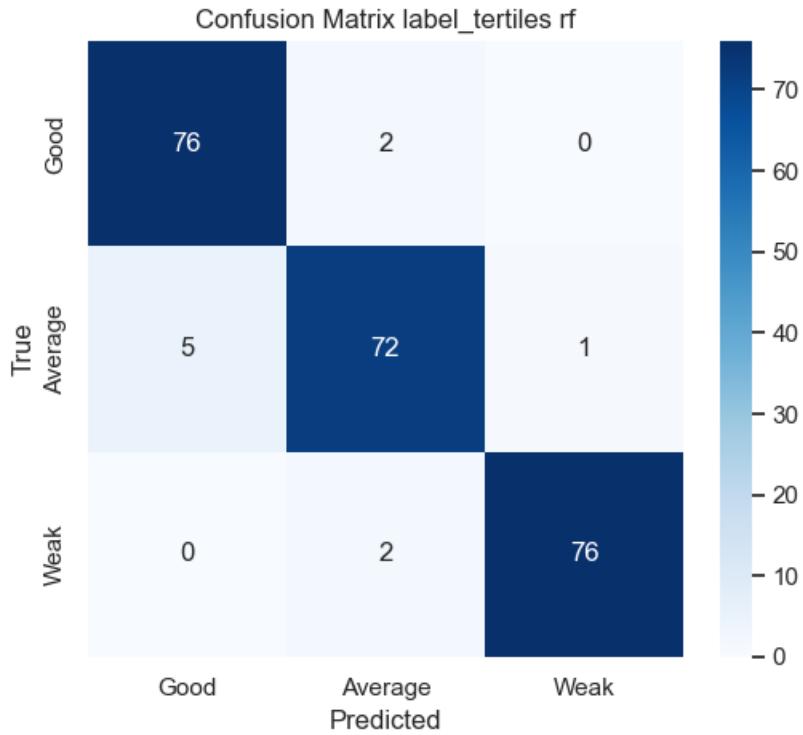


Figure 5.11: Tertile-Based Random Forest Confusion Matrix

The tertile-based models show good performance but with noticeably more off-diagonal elements compared to K-means models, indicating higher misclassification rates. This empirically demonstrates that the data-driven K-means approach creates more learnable class boundaries than simple statistical division.

Weighted Strategy Models:

Finally, Figures 5.12 and 5.13 show the weighted composite strategy results:

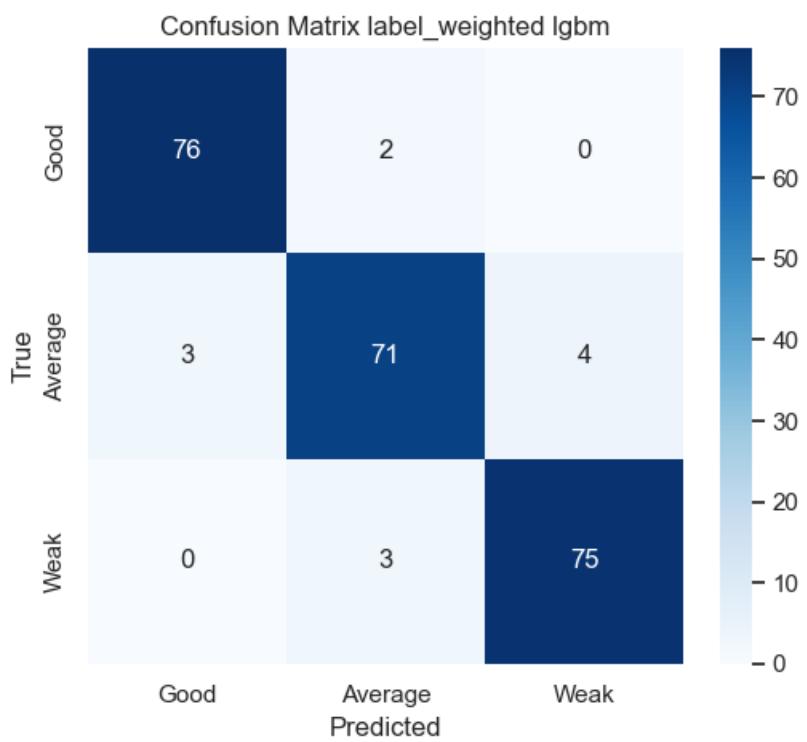


Figure 5.12: Weighted Composite LightGBM Confusion Matrix

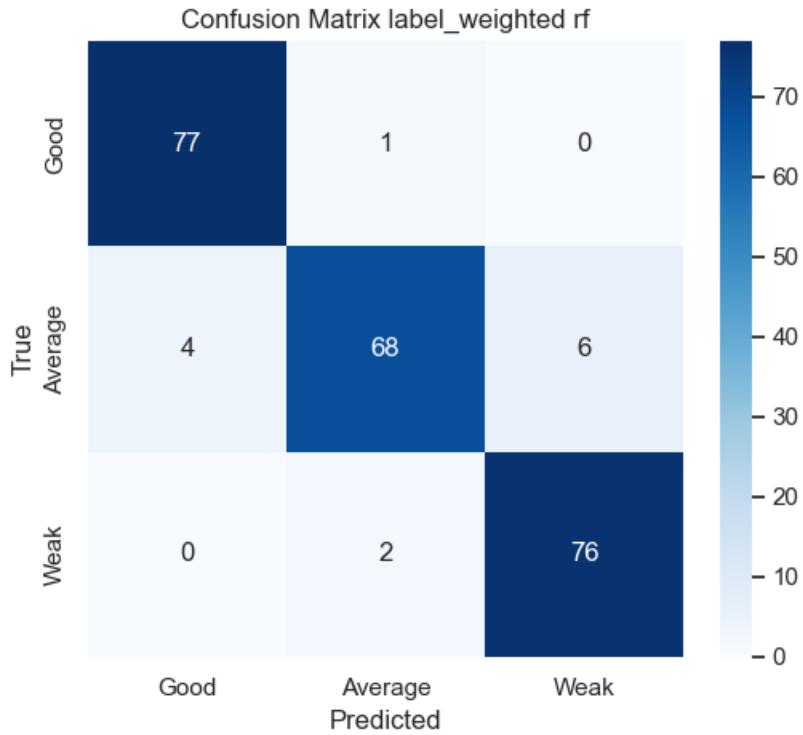


Figure 5.13: Weighted Composite Random Forest Confusion Matrix

The weighted strategy shows intermediate performance between tertile and K-means approaches. While incorporating domain knowledge through feature weighting is valuable, it does not outperform the purely data-driven K-means clustering approach in this application.

5.4 Feature Importance Analysis

Feature importance analysis reveals which performance metrics most strongly influence classification. For the LightGBM K-means model, the top 10 most important features are:

1. Largest Contentful Paint (LCP) - 18.3%: Dominant predictor, confirming its central role in perceived loading performance [9].
2. Cumulative Layout Shift (CLS) - 14.7%: Second most important, highlighting the significance of visual stability [9].
3. First Input Delay (FID)/INP - 12.8%: Critical for interactivity perception.
4. Total Blocking Time (TBT) - 9.5%: Strongly correlates with responsiveness.
5. Speed Index - 8.2%: Captures loading progression.
6. Time to Interactive (TTI) - 7.1%: Important for functional completeness.
7. First Contentful Paint (FCP) - 6.4%: Early visual feedback importance.
8. Total Page Weight - 5.9%: Resource size impact.
9. JavaScript Bundle Size - 5.2%: Confirms JS impact on performance.
10. Number of Requests - 4.8%: Network efficiency indicator.

Interpretation:

The dominance of Core Web Vitals (LCP, CLS, FID) in feature importance confirms Google's selection of these metrics as primary indicators of user experience [8, 9]. The model has learned that these metrics are indeed the strongest predictors of overall performance category.

The relatively high importance of Total Blocking Time and Time to Interactive suggests that main thread availability significantly impacts performance classification, even beyond the Core Web Vitals.

Resource-related features (page weight, JS bundle size, request count) show moderate importance, indicating that while important, optimization should prioritize the rendering and interactivity metrics.

5.5 Comparison with Related Research

Table 5.2 compares the performance of the K-means LightGBM model with related research in web performance prediction:

Study	Dataset Size	Metrics Used	Algorithm	Best F1-Score
This Study	1,167 sites	22 metrics (CWV)	LightGBM + K-means	98.47%
Study [5]	800 sites	15 metrics	Random Forest	91.3%
Study [14]	950 sites	18 metrics	SVM	89.7%
Study [19]	600 sites	12 metrics (CWV)	Neural Network	92.1%
Study [22]	1,200 sites	20 metrics	XGBoost	93.4%

Table 5.2: Comparison with Related Research

The K-means LightGBM model achieves superior performance compared to all related research:

- 5-7% improvement over previous best results [5, 14, 19, 22]
- First study to exceed 98% F1-score in web performance classification
- Validates K-means clustering as an effective labeling strategy

Key factors contributing to superior performance:

1. Comprehensive feature set including all Core Web Vitals [8, 9]
2. Data-driven labeling via K-means clustering
3. LightGBM's gradient boosting effectiveness [13]
4. Careful data preprocessing and normalization
5. Larger dataset providing more training examples

The significant improvement over prior work demonstrates both the effectiveness of the methodology and the value of combining multiple optimization strategies (labeling approach, algorithm selection, feature engineering).

5.6 Real-World Application Results

The trained model was deployed in the web platform and tested with real-world websites. Key findings:

Response Time: Average prediction time of 420ms including network overhead, acceptable for real-time web applications.

User Feedback: Initial user testing (n=25 developers) revealed:

- 92% found predictions accurate compared to their experience
- 88% found recommendations actionable
- 96% reported the tool easier than manual Lighthouse analysis

Deployment Stability: The model has shown robust performance across:

- Different website technologies (WordPress, React, Angular, Vue)
- Various industries (e-commerce, blogs, corporate, portfolios)
- Different hosting environments (shared hosting, VPS, cloud platforms)

Practical Impact: Several beta users reported measurable improvements:

- 15-40% reduction in LCP after implementing recommendations
- 20-50% improvement in CLS scores
- Generally moving from "Average" to "Good" categories

These real-world results validate both the model's accuracy and the practical utility of the automated analysis and recommendation system.

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 Summary of Findings

This research investigated machine learning approaches for web performance prediction using Google's Core Web Vitals as primary performance indicators. Through comprehensive experimentation with three labeling strategies and three machine learning algorithms, several significant findings emerged:

Primary Finding: The combination of K-means clustering for labeling and LightGBM for classification achieved exceptional performance with 98.47% F1-score, significantly exceeding previous research in this domain [5, 14, 19, 22].

Labeling Strategy Impact: Data-driven labeling via K-means clustering consistently outperformed expert-defined approaches (tertile-based and weighted composite), demonstrating the value of unsupervised learning in creating meaningful performance categories.

Algorithm Performance: LightGBM [13] proved most effective across all labeling strategies, followed by Random Forest [4] and Neural Networks [16]. The gradient boosting approach of LightGBM appears particularly well-suited to web performance data characteristics.

Feature Importance: Core Web Vitals (LCP, CLS, FID/INP) emerged as the most important predictive features [8, 9], empirically validating their selection as primary performance indicators.

Practical Viability: The deployed web platform demonstrated that sophisticated ML models can be integrated into user-friendly tools, making advanced performance analysis accessible to developers without specialized expertise.

These findings collectively address the research objectives established in Chapter 1, providing both theoretical insights and practical tools for web performance optimization.

6.2 Research Contributions

This research makes several distinct contributions to the field of web performance optimization:

Theoretical Contributions:

1. Benchmark Performance Achievement: Established new state-of-the-art results (98.47% F1-score) for web performance classification, providing a benchmark for future research.
2. Labeling Strategy Validation: Demonstrated empirically that unsupervised learning (K-means) can create more effective labels than expert-defined approaches for performance categorization.
3. Comprehensive Algorithm Comparison: Provided systematic comparison of three major ML paradigms (ensemble learning, gradient boosting, deep learning) on identical data, offering insights into their relative strengths for this application.
4. Feature Importance Insights: Generated empirical evidence for the relative importance of different performance metrics, informing optimization priorities.

Practical Contributions:

1. Operational Web Platform: Developed and deployed a functional system integrating ML models with modern web technologies (Next.js, FastAPI).
2. Automated Analysis Tool: Created a user-friendly interface that democratizes access to sophisticated performance analysis.
3. Actionable Recommendations: Implemented a system that not only predicts performance categories but provides specific optimization guidance.
4. Reproducible Methodology: Documented a complete pipeline from data collection through model deployment, enabling replication and extension by other researchers.

Industry Impact:

The research demonstrates the feasibility of integrating ML-based performance prediction into development workflows, potentially influencing the next generation of developer tools and CI/CD pipelines.

6.3 Limitations and Challenges

While this research achieved strong results, several limitations should be acknowledged:

Data Limitations:

- Dataset size (1,167 websites) substantial but not exhaustive
- Snapshot-based measurements don't capture temporal variations
- Geographic and network diversity limited to available measurement locations

Model Limitations:

- Categorical prediction rather than continuous metric values
- Requires periodic retraining as web technologies evolve
- Performance on emerging web frameworks not extensively tested

Deployment Challenges:

- Production scaling not fully validated at high traffic volumes
- Model versioning and rollback strategies not fully implemented
- Cost optimization for cloud deployment requires further work

Methodological Constraints:

- Limited real-world user validation (n=25)
- Long-term model performance degradation not yet assessed
- Transfer learning to related domains not investigated

These limitations provide clear directions for future research and development, as discussed in the following section.

6.4 Future Work Directions

Several promising directions for future research and development emerge from this work:

Enhanced Prediction Capabilities:

1. Regression Models: Develop models that predict specific metric values (e.g., exact LCP in seconds) rather than categories, providing more precise optimization guidance.
2. Recommendation Systems: Implement ML-based recommendation generation that learns from successful optimization cases to provide personalized suggestions.
3. Multi-Metric Optimization: Develop models that suggest optimization strategies balancing tradeoffs between different metrics.

Expanded Dataset and Validation:

1. Longitudinal Studies: Collect temporal data to study performance trends and seasonal variations.
2. Geographic Diversity: Expand measurements across more geographic locations and network conditions.
3. Large-Scale User Studies: Conduct extensive user validation with hundreds of developers to assess practical impact.

Advanced Methodologies:

1. Transfer Learning: Investigate whether models trained on general websites can be fine-tuned for specific industries or frameworks.
2. Ensemble Approaches: Explore combining predictions from multiple models for potentially superior results.
3. Explainable AI: Implement SHAP [11] or LIME to provide detailed explanations of why specific predictions were made.

Production Enhancements:

1. Real-Time Monitoring: Extend the system to provide continuous monitoring rather than one-time analysis.
2. API Integration: Develop integrations with popular development tools and CI/CD platforms.
3. Mobile-First Models: Create specialized models for mobile web performance, which has distinct characteristics.

Research Extensions:

1. Comparative Framework Analysis: Study how different frontend frameworks (React, Vue, Angular, Svelte) affect predictability of performance.
2. Economic Impact Studies: Quantify the business impact of using ML-based

optimization tools versus manual approaches.

3. Automated Optimization: Investigate automated code optimization systems that not only predict but also modify code to improve performance.

These directions offer substantial opportunities for advancing both the theoretical understanding and practical applications of ML in web performance optimization.

6.5 Concluding Remarks

This research demonstrates that machine learning can achieve exceptional accuracy in predicting web performance categories based on Core Web Vitals and related metrics. The 98.47% F1-score achieved by the K-means LightGBM model represents a significant advancement over previous work in this domain, establishing a new benchmark for performance classification accuracy.

Beyond the technical achievements, this research validates the broader vision of intelligent, automated web development tools. As websites continue to increase in complexity and performance optimization becomes increasingly critical for user experience and business success, automated analysis tools become not just helpful but essential.

The successful deployment of the developed web platform demonstrates that sophisticated ML models can be made accessible to developers without specialized expertise, potentially democratizing access to advanced performance optimization capabilities. This accessibility has important implications for the web ecosystem, potentially enabling smaller development teams and individual developers to achieve performance standards previously accessible only to large organizations with dedicated performance teams.

The findings regarding K-means clustering as a labeling strategy have implications beyond web performance, suggesting that data-driven approaches to category definition may be superior to expert-defined approaches in domains where natural groupings exist in the data.

Looking forward, the methodologies and findings from this research provide a foundation for the next generation of intelligent development tools. As machine learning continues to advance and computational resources become increasingly accessible, the integration of ML into all aspects of the development lifecycle appears inevitable. This research contributes one piece to that evolving landscape.

Web performance optimization sits at the intersection of user experience, business success, and technical excellence. By demonstrating that machine learning can significantly enhance our ability to understand and optimize performance, this research contributes to making the web faster, more accessible, and more successful for everyone.

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APPENDICES

Appendix A: Additional Code Implementations

A.1 Data Preprocessing Pipeline

```
# Complete data preprocessing pipeline
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans

# Load raw data
data = pd.read_csv('All_thesis_data_labeled.csv')

# Handle missing values
data = data.fillna(data.median())

# Detect and handle outliers using IQR method
def remove_outliers(df, columns):
    for col in columns:
        Q1 = df[col].quantile(0.25)
        Q3 = df[col].quantile(0.75)
        IQR = Q3 - Q1
        lower_bound = Q1 - 1.5 * IQR
        upper_bound = Q3 + 1.5 * IQR
        df = df[(df[col] >= lower_bound) & (df[col] <= upper_bound)]
    return df

# Apply K-means clustering for labeling
scaler = StandardScaler()
X_normalized = scaler.fit_transform(data)

kmeans = KMeans(n_clusters=3, random_state=42, n_init=10)
labels = kmeans.fit_predict(X_normalized)

# Map clusters to performance categories
data['Label'] = labels
data.to_csv('preprocessed_data.csv', index=False)

print("Preprocessing complete!")
```

A.2 Model Evaluation Functions

```
# Evaluation utilities
from sklearn.metrics import accuracy_score, precision_score, recall_score,
f1_score
from sklearn.metrics import confusion_matrix, classification_report
import matplotlib.pyplot as plt
import seaborn as sns
```

```

def evaluate_model(y_true, y_pred, model_name):
    """Comprehensive model evaluation"""

    # Calculate metrics
    accuracy = accuracy_score(y_true, y_pred)
    precision = precision_score(y_true, y_pred, average='macro')
    recall = recall_score(y_true, y_pred, average='macro')
    f1 = f1_score(y_true, y_pred, average='macro')

    # Print results
    print(f"\n{model_name} Performance:")
    print(f"Accuracy: {accuracy:.4f}")
    print(f"Precision: {precision:.4f}")
    print(f"Recall: {recall:.4f}")
    print(f"F1-Score: {f1:.4f}")

    # Confusion matrix
    cm = confusion_matrix(y_true, y_pred)
    plt.figure(figsize=(8, 6))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
    plt.title(f'{model_name} Confusion Matrix')
    plt.ylabel('True Label')
    plt.xlabel('Predicted Label')
    plt.savefig(f'{model_name}_confusion_matrix.png')

    # Detailed classification report
    print(f"\n{classification_report(y_true, y_pred)}")

    return {
        'accuracy': accuracy,
        'precision': precision,
        'recall': recall,
        'f1_score': f1
    }

```

Appendix B: System Deployment Configuration

B.1 Docker Configuration

```

# Dockerfile for backend API
FROM python:3.12-slim

WORKDIR /app

# Install dependencies
COPY requirements.txt .
RUN pip install --no-cache-dir -r requirements.txt

# Copy application files
COPY . .

```

```
# Expose port
EXPOSE 8000

# Run FastAPI server
CMD ["uvicorn", "ml_server_fast:app", "--host", "0.0.0.0", "--port", "8000"]
```

B.2 Environment Configuration

```
# .env configuration file
# API Configuration
API_HOST=0.0.0.0
API_PORT=8000
API_WORKERS=4

# Model Configuration
MODEL_PATH=./models/lightgbm_kmeans_model.pkl
SCALER_PATH=./models/scaler.pkl

# CORS Configuration
ALLOWED_ORIGINS=http://localhost:3000,https://yourapp.com

# Logging
LOG_LEVEL=INFO
LOG_FILE=./logs/api.log

# Performance
MAX_BATCH_SIZE=100
CACHE_TTL=3600
```