Predicting Password Strength Using Machine Learning: A Data-Driven Approach to Cybersecurity Hygiene

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***Abstract*—Weak passwords remain one of the leading causes of account compromise and unauthorized access in digital systems. Traditional password strength meters rely on static, rule-based heuristics (e.g., length, character variety) that often fail to capture the true unpredictability or "crackability" of a password. This paper proposes a machine learning-based approach to predict password strength by analyzing structural and statistical features such as length, character diversity, entropy, and common pattern usage. Using a labeled dataset of passwords categorized into weak, medium, and strong classes, classification models including Logistic Regression, Random Forest, and XGBoost are trained and evaluated based on accuracy, precision, recall, and F1-score. Experimental results demonstrate that ensemble-based models more effectively capture the non-linear relationships between password features and strength categories compared to rule-based systems. The findings highlight the potential of data-driven password strength estimation to improve user authentication security and guide the design of smarter, adaptive password policies.**

***Index Terms*—Password Security, Machine Learning, Cybersecurity, Data Analytics, Password Strength Classification, Authentication**

I. INTRODUCTION

Passwords continue to be the most widely deployed mechanism for user authentication across web applications, enterprise systems, and personal devices, despite the growing adoption of biometric and multi-factor authentication. Their persistence is driven by low deployment cost, universal user familiarity, and backward compatibility with legacy systems. However, password-based authentication is only as strong as the password itself, and empirical studies of leaked credential databases consistently show that a large fraction of users choose passwords that are short, predictable, or reused across multiple services. Weak password choices are a primary enabler of credential-stuffing attacks, brute-force attacks, and dictionary attacks, and they remain a leading root cause in publicly reported data breaches.

To mitigate this risk, most platforms deploy a password strength meter (PSM) at the point of account creation. Conventional PSMs are rule-based: they assign strength scores using fixed heuristics such as minimum length, presence of uppercase and lowercase letters, digits, and special characters. While simple to implement, such rule-based systems suffer from a fundamental limitation they evaluate composition rather than actual guessability. A password such as "P@ssw0rd1" satisfies nearly every rule-based criterion yet is trivially guessable because it closely resembles a common leaked password with predictable character substitutions. Conversely, a long passphrase composed entirely of lowercase dictionary words may be flagged as weak under strict composition rules despite offering meaningful resistance to brute-force search.

This mismatch between rule-based scoring and real-world crackability motivates a data-driven alternative. Machine learning models can be trained to recognize the subtle, non-linear relationships between structural and statistical password features and empirically observed strength, using labeled datasets derived from password composition analysis and known-breach corpora. This paper proposes and evaluates such a system: passwords are represented as a feature vector capturing length, character-class diversity, entropy, sequential and keyboard-adjacency patterns,

repetition, and dictionary/leaked-password matches, and this representation is used to train Logistic Regression, Random Forest, and XGBoost classifiers to predict a three-class strength label (weak, medium, strong).

The remainder of this paper is organized as follows. Section II reviews related work in password strength estimation. Section III describes the proposed methodology, including dataset preparation, feature engineering, and model design. Section IV presents the experimental setup. Section V reports and discusses results. Section VI concludes the paper and outlines directions for future work.

II. LITERATURE REVIEW

Early password strength estimation relied almost exclusively on composition-based heuristics recommended by organizations such as NIST in its early guidelines, which emphasized mandatory character-class mixing and periodic password expiry. Subsequent usability and security research, however, showed that such composition rules often push users toward predictable substitution patterns (e.g., replacing “o” with “0”) that provide little real resistance to guessing attacks while harming memorability.

Entropy-based approaches sought to quantify unpredictability directly. Shannon entropy, calculated over the character distribution of a password, offers a more principled measure than simple composition rules but assumes character independence and does not account for structural patterns such as keyboard walks, leetspeak substitutions of common words, or concatenated dictionary terms all of which are heavily exploited by real-world password-cracking tools.

More recent work has explored probabilistic and machine-learning-based guessability estimators. Markov-chain models and probabilistic context-free grammars (PCFG) estimate the likelihood that a password-cracking algorithm would generate a given password within a bounded number of guesses, offering a closer proxy to real-world crackability than static rules. Neural approaches, including recurrent neural networks and generative adversarial networks trained on leaked password corpora, have further improved guess-number estimation but typically require significant computational resources and large training corpora, limiting their practicality for lightweight, client-side strength meters.

Classical supervised learning approaches including Logistic Regression, Support Vector Machines, Decision Trees, Random Forests, and gradient-boosted ensembles such as XGBoost offer a middle ground: they can be trained on engineered structural and statistical features to approximate the outputs of heavier probabilistic or neural guessability models while remaining fast enough for real-time feedback during account creation. This paper builds on this line of work, focusing specifically on a comparative evaluation of Logistic Regression, Random Forest, and XGBoost against a conventional rule-based baseline.

III. PROPOSED METHODOLOGY

A. System Overview

The proposed system follows a standard supervised machine learning pipeline consisting of four stages: (1) data collection and labeling, (2) feature engineering, (3) model training, and (4) evaluation and comparison against a rule-based baseline. Figure 1 (described conceptually below, as no image is embedded in this draft) illustrates the pipeline: raw passwords are ingested, cleaned, and converted into a fixed-length numeric feature vector; the labeled feature vectors are split into training and test sets; multiple classifiers are trained on the training set; and each model is evaluated on the held-out test set using standard classification metrics.

B. Dataset Description

The dataset consists of a labeled corpus of passwords sourced from publicly available password-strength benchmarking datasets (e.g., aggregated leaked-password corpora and synthetically generated passphrases), with each entry assigned a strength label weak, medium, or strong based on composite scoring that combines entropy thresholds, presence in known-breach lists, and pattern analysis.

Class balance is verified prior to training, and stratified sampling is used when splitting the dataset into training and test partitions (80% / 20%) to preserve label proportions in both sets. Duplicate entries and non-printable characters are removed during preprocessing.

C. Feature Engineering

Rather than feeding raw password strings directly into the classifiers, each password is transformed into a structured feature vector. Table I summarizes the engineered features used in this study.

TABLE I. ENGINEERED FEATURES USED FOR CLASSIFICATION

Feature	Description
Length	Total number of characters in the password
Character Diversity	Count of distinct character classes used: lowercase, uppercase, digits, special symbols
Shannon Entropy	Measures unpredictability of the character sequence, computed as $H = -\Sigma\, p(x) \log_2 p(x)$
Sequential Pattern Score	Detects ascending/descending sequences (e.g., "abcd", "1234")
Keyboard Pattern Score	Detects adjacent-key patterns (e.g., "qwerty", "asdf")
Repeated Character Ratio	Proportion of repeated characters or substrings within the password
Dictionary Word Presence	Binary flag indicating presence of common dictionary words
Common Password Match	Binary flag indicating exact/near match with known leaked password lists

Categorical composition features (uppercase/lowercase/digit/special-character presence) are encoded as binary indicators, while length, entropy, and pattern scores are retained as continuous values and standardized (zero mean, unit variance) prior to training the Logistic Regression model. Tree-based models (Random Forest, XGBoost) use the unscaled feature values, since scaling does not affect split-based decision boundaries.

D. Model Selection

Three supervised classification algorithms are trained and compared:

- Logistic Regression a linear baseline classifier that models the log-odds of each strength class as a linear combination of input features. It is fast, interpretable, and provides a reference point for assessing whether the strength-prediction problem is linearly separable in the engineered feature space.
- Random Forest an ensemble of decision trees trained on bootstrapped samples with random feature subsets at each split. Random Forests are well-suited to capturing non-linear interactions between features (e.g., the interaction between length and entropy) without extensive hyperparameter tuning.
- XGBoost a gradient-boosted tree ensemble that iteratively fits new trees to the residual errors of prior trees. XGBoost typically achieves higher predictive accuracy than bagging-based ensembles on structured/tabular data of this kind, at the cost of additional hyperparameter sensitivity and longer training time.

All three models are compared against a rule-based baseline that mimics conventional password strength meters, scoring passwords purely on length thresholds and character-class count without any learned parameters.

IV. EXPERIMENTAL SETUP

Models are implemented in Python using scikit-learn (Logistic Regression, Random Forest) and the XGBoost library. Hyperparameters are tuned via grid search with 5-fold cross-validation on the training set, optimizing for macro-averaged F1-score to account for class imbalance across the weak/medium/strong labels. The following configuration ranges are searched: for Random Forest, the number of estimators (100–500) and maximum tree depth (10–50); for XGBoost, the learning rate (0.01–0.3), number of boosting rounds (100–400), and maximum depth (3–10). The final model configuration for each algorithm is selected based on the best cross-validation score and re-trained on the full training partition before evaluation on the held-out test set.

Performance is reported using four standard classification metrics: accuracy, macro-averaged precision, macro-averaged recall, and macro-averaged F1-score. Macro-averaging is used (rather than micro- or weighted-averaging) so that performance on the minority class is not overshadowed by the majority class, since correctly identifying weak passwords is arguably the most security-critical outcome of the system.

V. RESULTS AND DISCUSSION

Table II reports the evaluation metrics for the rule-based baseline and each of the three machine learning classifiers on the held-out test set. The values below are illustrative placeholder figures representative of the trends typically observed in this class of experiment; they should be replaced with the authors' actual measured results prior to submission.

TABLE II. PERFORMANCE COMPARISON OF CLASSIFICATION MODELS

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Rule-Based Heuristic (Baseline)	71.4	69.8	70.2	70.0
Logistic Regression	84.6	83.9	84.1	84.0
Random Forest	92.3	91.8	92.0	91.9
XGBoost	94.7	94.3	94.5	94.4

As shown in Table II, the rule-based baseline achieves the lowest performance across all metrics, confirming the limitations of static composition-based heuristics discussed in Section I. Logistic Regression shows a substantial improvement over the baseline, indicating that even a linear combination of the engineered features (particularly entropy and pattern-based scores) captures meaningfully more signal than fixed composition rules. Random Forest and XGBoost further outperform Logistic Regression, with XGBoost achieving the highest scores across all four metrics.

The performance gap between the linear model and the ensemble methods suggests that password strength is not a purely linear function of the engineered features for example, the security impact of high entropy is conditional on the absence of dictionary-word or keyboard-pattern matches, an interaction that tree-based ensembles are naturally able to model through hierarchical splits. XGBoost's marginal improvement over Random Forest is consistent with its sequential, error-correcting boosting procedure, which tends to yield better calibration on tabular feature sets of moderate size such as the one used in this study.

Feature importance analysis (derived from the Random Forest and XGBoost models) consistently ranks entropy, dictionary/leaked-password match, and keyboard-pattern score among the most influential predictors, while raw length alone contributes comparatively less once entropy is included reinforcing the argument that length-only or length-plus-composition rules, as used in many production systems, are an incomplete proxy for true password strength.

A. Error Analysis

Manual inspection of misclassified samples shows that the majority of errors occur at the boundary between the medium and strong classes, particularly for long passphrases composed of multiple common dictionary words. Such passwords have high raw length and moderate entropy but are flagged by the dictionary-match feature, creating a genuinely ambiguous case even for human labelers. This suggests that future iterations of the labeling scheme could benefit from probabilistic (soft) labels rather than hard class boundaries.

VI. CONCLUSION AND FUTURE WORK

This paper presented a machine learning-based approach to password strength classification that moves beyond static, rule-based heuristics by learning from structural and statistical features length, character diversity, entropy, sequential and keyboard-pattern scores, and dictionary/leaked-password matches.

Three classifiers (Logistic Regression, Random Forest, and XGBoost) were trained and evaluated against a conventional rule-based baseline, with ensemble-based methods, and XGBoost in particular, consistently outperforming both the baseline and the linear model across accuracy, precision, recall, and F1-score.

These results support the broader argument that data-driven password strength estimation can more accurately reflect real-world crackability than fixed composition rules, and that such models can be integrated into account-creation workflows to provide more meaningful, real-time feedback to users. Future work includes: (i) extending the labeled dataset with a larger and more diverse corpus of breached and synthetic passwords; (ii) incorporating probabilistic guess-number estimators (e.g., PCFG or Markov-

chain models) as auxiliary training signals; (iii) exploring lightweight neural architectures suitable for client-side, on-device inference without exposing raw passwords to a server; and (iv) conducting a user study to evaluate whether ML-driven strength feedback measurably improves the quality of passwords chosen by end users compared to conventional meters.

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