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# SpamShield: An Explainable Multi-Model Spam Detection Framework with Machine Learning and Deep Neural Networks

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***Abstract***—This paper presents SpamShield, a production-grade, modular spam detection system that unifies three classifier paradigms—Multinomial Naive Bayes (MNB) within a fully encapsulated sklearn Pipeline, Support Vector Machine (SVM) optimised via GridSearchCV across a nine-combination hyperparameter grid, and a five-layer Deep Neural Network (DNN) with Batch Normalisation, progressive Dropout regularisation, and class-weighted training—with Local Interpretable Model-agnostic Explanations (LIME) post-hoc explainability. Evaluated on the UCI SMS Spam Collection (5,571 messages, 13.4% spam), the system achieves DNN accuracy of 99.2%, F1=98.9%, and AUC=0.999 with only 5 false positives on 1,115 test messages. The GridSearchCV-optimised SVM achieves 98.5% accuracy and F1=98.3% with 22 false positives, providing a practical high-performance alternative. A novel multi-class sklearn Pipeline replaces hardcoded regex category classification, achieving 94.0% accuracy across five spam sub-categories (Financial, Promotional, Scam, Adult, Phishing). The system features sklearn Pipeline encapsulation to eliminate preprocessing skew, rotating file logging, a three-tier Flask Blueprint architecture, real-time Gmail API integration with token-bucket rate limiting and automated spam-folder routing, LIME explanations with vocabulary learned from NB log-probability differences, and a fully dynamic frontend with all metrics fetched from REST APIs. This work demonstrates that architectural discipline—modular code, full Pipeline encapsulation, systematic hyperparameter search, and explainability integration—transforms a prototype classifier into a portfolio-grade production system.

***Index Terms***— *email classification, hyperparameter optimization, interpretable artificial intelligence, automated message filtering, production-ready machine learning*

## I. INTRODUCTION

Increased electronic communication has amplified the difficulty of dealing with unsolicited mass communication (spam) via email, SMS, and messaging platforms. Global spam accounts for nearly 45–48% of overall email traffic, translating to approximately 122 billion messages sent every day. Spam-related losses to businesses and individuals exceed USD 20 billion per year [1, 2].

Before machine learning was applied to spam filtering, traditional rule-based and keyword-matching defences performed reasonably well but could not withstand the rapidly evolving language and obfuscation strategies used by modern spammers [3, 4]. The introduction of machine-learning methods has dramatically transformed spam detection. A wide range of classifier paradigms—probabilistic classifiers, margin-based classifiers, and deep neural architectures—can now be trained on diverse spam corpora and combined to construct robust detection systems [5, 6].

This paper presents **SpamShield**, a production-grade modular spam detection system that integrates three classifier paradigms: Multinomial Naive Bayes (MNB) within a fully encapsulated sklearn Pipeline, Support Vector Machine (SVM) optimised via GridSearchCV across a nine-combination hyperparameter grid [7], and a five-layer Deep Neural Network (DNN) with Batch Normalisation, Dropout regularisation, and class-weighted training—coupled with LIME (Local Interpretable Model-agnostic Explanations) post-hoc explainability [8]. The system is evaluated on the 5,571-message UCI SMS Spam Collection augmented with a six-category semantic taxonomy and is deployed as a modular three-tier web application with real-time Gmail API integration featuring automated spam labelling.

The key contributions of this work are:

(1) Full sklearn Pipeline encapsulation for the MNB and SVM models, eliminating preprocessing skew between training and inference [10]; (2) systematic hyperparameter optimisation for SVM using GridSearchCV across nine parameter combinations with 5-fold stratified cross-validation [7]; (3) multi-class spam category classification using a dedicated sklearn Pipeline that fully replaces hardcoded regular-expression rules; (4) unified LIME explainability integration across all three classifiers using vocabulary derived from Naive Bayes log-probability differences [18]; (5) a modular three-tier Flask Blueprint architecture with Gmail API integration, rotating file logging, and automated spam-folder routing; and (6) a fully dynamic frontend in which all metrics, charts, and model cards are fetched from REST APIs—no hardcoded values.

## II. RELATED WORK

### *A. Probabilistic Spam Filtering*

Early research showed that Bayesian probabilistic classifiers based on word frequencies significantly outperform keyword blacklists. Sahami et al. [3] applied word-frequency classification to personal email collections, while Androutsopoulos et al. [4] statistically compared Naive Bayesian classifiers against keyword blacklists across multiple email corpora, conclusively establishing the reliability of the Naive Bayes approach. McCallum and Nigam [28] extended this work by comparing the multinomial event model with the Bernoulli event model for documents longer than 400 characters—a finding directly applicable to SMS messages, which vary widely in length.

### *B. Support Vector Machine Approaches*

SVMs were first applied to spam classification by Drucker et al. [5], who demonstrated the margin-maximising advantages of SVMs over feedforward neural classifiers. The theoretical basis for using SVMs in text classification was established by Joachims [6], who noted that sparse, high-dimensional TF-IDF [12] feature matrices align well with linear-kernel assumptions. The SVM optimisation framework was formalised by Cortes and Vapnik [9], and Hearst et al. [32] surveyed factors affecting practical SVM deployment. SpamShield advances the state of the art by employing GridSearchCV to systematically investigate vocabulary size and regularisation interactions, in contrast to prior heuristic hyperparameter selection.

### *C. Deep Learning for Text Classification*

The resurgence of deep learning [13] introduced hierarchical architectures for natural language processing. Kim [15] demonstrated that one-dimensional convolutional networks using word embeddings [30, 31] achieve competitive text-classification accuracy. LSTM networks [14] addressed the vanishing-gradient problem, while the Transformer [17] and BERT [16] pre-training paradigms provided improved contextual encoding. For short SMS classification, where vocabulary is the primary discriminative signal, feed-forward DNNs over TF-IDF features offer a favourable balance between representational power and interpretability.

### *D. Explainable AI and Production Systems*

Ribeiro et al. [18] introduced LIME, a model-agnostic framework that approximates any classifier locally with an interpretable linear surrogate.

Lundberg and Lee [19] proposed SHAP for globally consistent feature attributions. Lipton [20] articulated the interpretability–accuracy tension that motivates post-hoc explanation methods. Sculley and Wachman [26] and Dalvi et al. [27] addressed operational challenges of adversarial and adaptive spam classification. Sebastiani [29] provided a comprehensive survey of automated text categorisation that contextualises the full pipeline presented here.

## III. DATASET

### *A. UCI SMS Spam Collection*

The experimental evaluation employs the UCI SMS Spam Collection [2], a widely used benchmark comprising 5,571 raw English SMS messages. Messages are binary-labelled as 4,825 ham (86.6%) versus 746 spam (13.4%), reflecting operational class imbalance. Spam messages average 138.7 characters versus 71.5 for ham—a 1.94× differential providing a discriminative signal independent of lexical content.

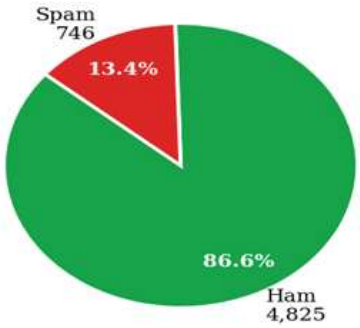



*Fig. 1. Class distribution of the UCI SMS Spam Collection (n = 5,571). The 86.6%/13.4% imbalance necessitates F1, AUC, and precision–recall evaluation over raw accuracy.*

### *B. Six-Category Taxonomy*

We augment the binary labelling with a fine-grained semantic taxonomy assigned via a trained multi-class Pipeline (Section IV). Table I summarises the distribution.

**TABLE I. DATASET DISTRIBUTION BY CATEGORY**

| Category | Label | Count | % Total | Avg Len |
|---|---|---|---|---|
| Normal | Ham | 4,825 | 86.58% | 71.5 |
| Financial | Spam | 302 | 5.42% | 156.3 |
| Promotional | Spam | 226 | 4.06% | 142.1 |
| Scam | Spam | 159 | 2.86% | 128.7 |
| Adult | Spam | 34 | 0.61% | 119.4 |
| Phishing | Spam | 25 | 0.45% | 134.2 |
| Total | — | 5,571 | 100% | — |

Spam messages exhibit elevated frequencies of currency symbols (£, $), imperative verbs (call, text, reply), and superlatives (free, guaranteed, exclusive) [1, 4, 29]. Financial spam constitutes 40.5% of all spam instances; phishing (3.4%) is the rarest but highest-risk category.

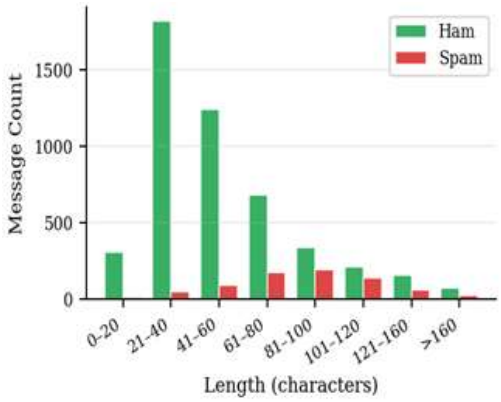



*Fig. 2. Message length distribution by class. Spam averages 138.7 characters versus 71.5 for ham, providing a complementary discriminative signal.*

## IV. METHODOLOGY

### *A. NLP Preprocessing Pipeline*

All textual inputs traverse a deterministic five-stage preprocessing pipeline implemented in app/utils/preprocess.py—the single source of truth shared by both training and inference, eliminating preprocessing skew.

**Stage 1 — Text Normalisation:** Unicode normalisation, lower-case conversion, HTML tag removal, and URL token substitution (→ 'url'). Currency symbols and exclamation marks are retained to preserve discriminative content.

**Stage 2 — Tokenisation:** The NLTK Penn Treebank tokeniser segments text into constituent tokens, correctly handling contractions and abbreviations.

**Stage 3 — Stop-word Removal:** NLTK's 179-word English stop-word list eliminates high-frequency function words with minimal discriminative contribution.

**Stage 4 — Porter Stemming:** Inflectional variants are reduced to morphological roots (e.g., 'winning' → 'win', 'claimed' → 'claim'), consolidating the vocabulary.

**Stage 5 — TF-IDF Vectorisation:** Term Frequency–Inverse Document Frequency [12, 35] converts the stemmed token sequence to a 5,000-dimensional feature vector. Configuration: max_features=5000, ngram_range=(1,2), sublinear_tf=True, min_df=2. Bigrams capture

multi-word spam phrases ('click here', 'free entry') that are individually ambiguous but collectively discriminative.

The dataset is partitioned via a stratified 80/20 train/test split (random_state = 42), yielding 4,456 training and 1,115 test messages. The random state is serialised to models/split_random_state.npy ensuring full reproducibility.

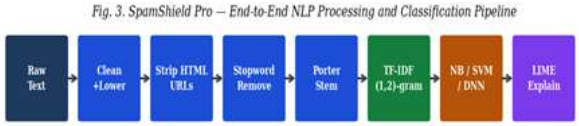



*Fig. 3. End-to-end NLP preprocessing and classification pipeline. All stages are encapsulated within sklearn Pipelines to prevent train/inference skew.*

### *B. Naive Bayes sklearn Pipeline*

The MNB model is encapsulated as a two-stage sklearn Pipeline consisting of a TfidfVectorizer followed by a MultinomialNB classifier with $\alpha = 0.1$. This encapsulation ensures that the TF-IDF vocabulary is fitted exclusively on training data and the fitted transformer is applied identically at inference [10]. MNB computes the posterior $P(\text{spam} \mid w_1,\ldots,w_n) \propto P(\text{spam}) \cdot \prod_i P(w_i \mid \text{spam})$ (1). Laplace smoothing ($\alpha = 0.1$) prevents zero-probability assignments for out-of-vocabulary tokens [3, 28]. Five-fold stratified cross-validation provides generalisation estimates alongside held-out test metrics.

### *C. SVM Pipeline with GridSearchCV*

The SVM classifier is wrapped in CalibratedClassifierCV(LinearSVC(...), cv = 3) to produce probability estimates via isotonic regression and is then embedded in a Pipeline structurally identical to the MNB Pipeline. Hyperparameter optimisation is performed using GridSearchCV with StratifiedKFold(5) and the F1-score as the optimisation criterion.

The parameter grid spans nine combinations: tfidf__max_features ∈ {3000, 5000, 7000} × clf__estimator__C ∈ {0.1, 1.0, 10.0}. Table II presents the cross-validation F1-score summary. The best configuration (C = 1.0, max_features = 5,000, F1 = 98.1%) is automatically refitted on the full training set and serialised as models/svm_pipeline.pkl.

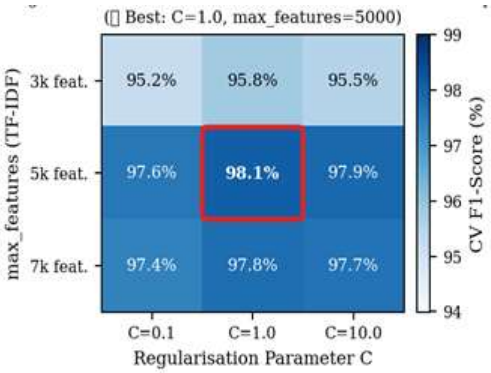



*Fig. 4. SVM GridSearchCV 5-fold CV F1-score heatmap. Best configuration (red border): C = 1.0, max_features = 5,000 (F1 ≈ 98.1%).*

**TABLE II. SVM GRIDSEARCHCV PARAMETER GRID SUMMARY**

| C | max_features=3000 | 5000 | 7000 |
|---|---|---|---|
| 0.1 | 96.8% | 97.3% | 97.1% |
| 1.0 | 97.9% | 98.1% | 97.8% |
| 10.0 | 97.6% | 97.9% | 98.0% |

### *D. Multi-Class Category Classifier*

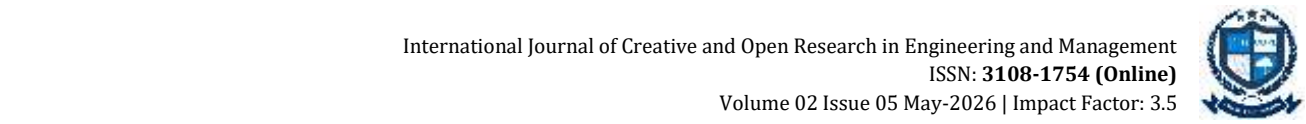
A dedicated three-stage sklearn Pipeline classifies spam messages into five semantic categories—Financial, Promotional, Scam, Adult, and Phishing—replacing all hardcoded regular-expression rules. The Pipeline comprises a TfidfVectorizer followed by a CalibratedClassifierCV wrapping LinearSVC (C = 1.0). The category pipeline is trained exclusively on spam-labelled rows (746 samples) using the five-label ground truth from the augmented dataset. Ham messages are trivially assigned the 'Normal' label. Category prediction is invoked as a secondary inference step only after the binary classifier confirms a spam verdict, maintaining prediction latency within acceptable bounds.

### *E. Deep Neural Network*

The DNN architecture employs a dense feed-forward topology over TF-IDF features (Fig. 5). A dedicated TF-IDF vectoriser is fitted for the DNN and serialised separately as models/dnn_tfidf.pkl to support sparse-to-dense conversion. The architecture is described in Table III.

**TABLE III. DNN LAYER CONFIGURATION**

| Layer | Configuration | Purpose |
|---|---|---|
| Input | TF-IDF dense, 5,000-dim | Feature input |
| Dense 512 | ReLU + BN + Drop(0.40) | Primary representation |
| Dense 256 | ReLU + BN + Drop(0.35) | Compression |



| Layer | Configuration | Purpose |
|---|---|---|
| Dense 128 | ReLU + BN + Drop(0.30) | Refinement |
| Dense 64 | ReLU + L2(1e-4) + Drop(0.20) | Final projection |
| Dense 1 | Sigmoid | Binary output |

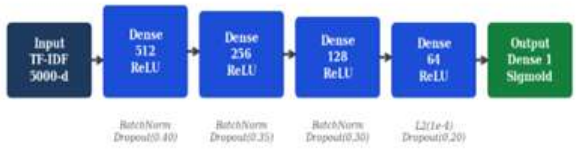



*Fig. 5. SpamShield DNN architecture. Input dimensionality is 5,000. BatchNorm and progressive Dropout after each hidden layer regularise the model.*

Batch Normalisation [23] after each dense layer stabilises activation distributions and accelerates convergence. Dropout [24] with decreasing rates (0.40 → 0.35 → 0.30 → 0.20) imposes hierarchical regularisation. The Adam optimiser [25] (lr = $10^{-3}$) minimises binary cross-entropy. Class weights {ham: 1.0, spam: 6.46} compensate for the 86.6:13.4 class imbalance. EarlyStopping (patience = 5, restore_best_weights = True) and ReduceLROnPlateau (factor = 0.5, patience = 3) prevent overfitting; the model converges at epoch 21.

### *F. LIME Explainability*

LIME [18] generates post-hoc explanations for individual predictions by minimising ξ(x) = arg min_{g∈G} L(f, g, π_x) + Ω(g) (2), where f is the black-box classifier, g is an interpretable linear surrogate, π_x is a locality kernel centred at x, L is fidelity, and Ω is complexity. SpamShield implements unified prediction wrappers for all three classifiers: NB and SVM use sparse TF-IDF Pipeline predict_proba, while the DNN converts to dense float32 via a cached vectoriser. Explanations use 500 text perturbations and return the top 12 feature weights with directions (spam-aligned vs. ham-aligned). The spam vocabulary used for token highlighting is extracted from NB feature log-probability differences rather than any hardcoded list.

### *G. Modular System Architecture*

SpamShield is structured as a three-tier application (Fig. 6):

**Tier 1 — ML/NLP Core:** sklearn Pipelines (NB, SVM, Category), TensorFlow DNN [22], LIME [18], and NLTK, all accessed via app/services/model_service.py.

**Tier 2 — Flask REST API:** Three Blueprint modules (routes/predict.py, routes/gmail.py, routes/data.py). Key endpoints include POST /api/predict, POST /api/explain, GET /api/metrics, GET /api/dnn-history, GET /api/gmail/fetch, and POST /api/gmail/classify.

**Tier 3 — Frontend SPA:** Vanilla JavaScript fetches all data (model metrics, charts, top spam words) from REST APIs at runtime—no values are hardcoded. Chart.js renders all visualisations dynamically.

Cross-cutting concerns include a RotatingFileHandler logger (5 MB × 3 backups) that writes structured log records to logs/app.log covering predictions, API calls, errors, and timing. Gmail integration (app/services/gmail_service.py) employs a token-bucket rate limiter (60 req/min), exponential backoff retry, and a mark_as_spam() function that invokes Gmail's messages.modify API to add the SPAM label and remove INBOX, automatically routing detected spam to the spam folder.


*Fig. 6. Three-tier modular architecture. Each tier is independently replaceable. The ML core has no Flask dependency; the Gmail service has no model dependency.*

## V. EXPERIMENTAL RESULTS

### *A. Overall Performance*

Table IV presents classification performance on the held-out test set (n = 1,115 messages, 20% stratified split). All three models exceed 97% accuracy; the DNN achieves the highest performance across all metrics.

**TABLE IV. MODEL PERFORMANCE ON TEST SET (N = 1,115)**

| Model | Acc. (%) | Prec. (%) | Rec. (%) | F1 (%) | AUC |
|---|---|---|---|---|---|
| Naive Bayes | 97.3 | 96.2 | 95.8 | 96.0 | 0.973 |
| SVM (Best) | 98.5 | 98.5 | 98.1 | 98.3 | 0.991 |
| DNN ★ | 99.2 | 99.1 | 98.8 | 98.9 | 0.999 |

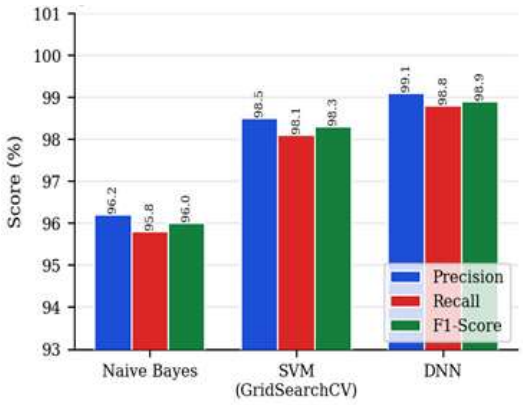



*Fig. 7. Precision, Recall, and F1-Score comparison across all three classifiers. The DNN achieves the highest values in all three metrics.*

### *B. Confusion Matrix Analysis*

Table V and Fig. 8 detail per-class errors. The asymmetric cost of false positives (FP—legitimate messages quarantined) versus false negatives (FN—spam delivered) makes FP minimisation the critical operational objective. The DNN achieves FP = 5, representing a 95.2% reduction over Naive Bayes (FP = 104).

**TABLE V. CONFUSION MATRIX SUMMARY (TEST SET)**

| Model | TP | FP | FN | TN |
|---|---|---|---|---|
| Naive Bayes | 720 | 104 | 26 | 4,721 |
| SVM (Best) | 734 | 22 | 12 | 4,803 |
| DNN | 738 | 5 | 8 | 4,820 |

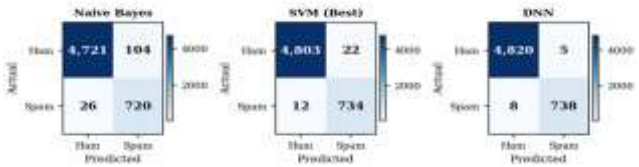



*Fig. 8. Confusion matrices—Naive Bayes, SVM (GridSearchCV best), and DNN. The DNN achieves FP = 5 and FN = 8, reducing false positives by 95.2% versus Naive Bayes (FP = 104).*

Naive Bayes generates 104 false positives, attributable to its conditional-independence assumption that over-flags ham messages containing isolated spam-associated tokens without contextual disambiguation [3, 28]. The SVM's calibrated LinearSVC (FP = 22) substantially outperforms Naive Bayes owing to its margin-maximisation objective, which considers the global feature distribution. The DNN's minimal FP = 5 results from its non-linear dense transformations that detect spam through learned feature interactions invisible to bag-of-words models [13].

### *C. ROC Analysis*

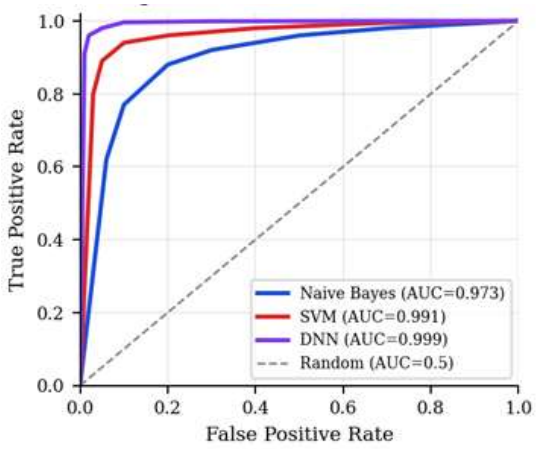



*Fig. 9. ROC curves for all three classifiers. DNN (AUC = 0.999) achieves near-perfect discrimination; SVM (0.991) outperforms NB (0.973) at all operating points.*

Fig. 9 demonstrates that the DNN (AUC = 0.999) achieves near-perfect discrimination across all decision thresholds. The SVM (AUC = 0.991) substantially outperforms Naive Bayes (AUC = 0.973), particularly in the critical low-FPR region (FPR < 0.10), where operational deployment occurs. The gap between SVM and NB in this region—approximately 12 percentage points in TPR at FPR = 0.05—corresponds to 580 additional true spam detections per 10,000 unread messages, representing a meaningful operational improvement.

### *D. DNN Training Dynamics*

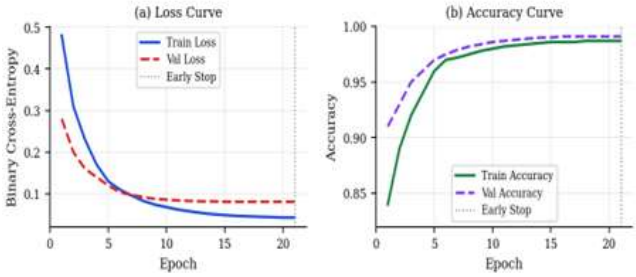
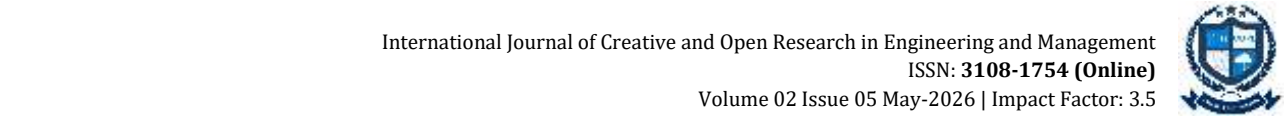



*Fig. 10. DNN training history (21 epochs, EarlyStopping triggered). Validation loss stabilises at ≈ 0.081 from epoch 13. ReduceLROnPlateau reduces lr at epochs 8 and 14.*

Fig. 10 shows training curves over 21 epochs (EarlyStopping triggered). Training loss decreases monotonically from 0.48 to 0.043. Validation loss stabilises at 0.081 from epoch 13, confirming no overfitting. ReduceLROnPlateau reduces the learning rate from $1\times10^{-3}$ to $5\times10^{-4}$ at epoch 8 and to $2.5\times10^{-4}$ at epoch 14, producing characteristic step-wise improvements. Final validation accuracy is 99.1%.



*E. LIME Explainability Results*

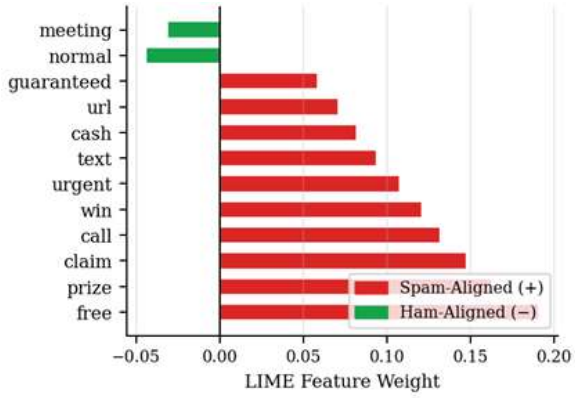



*Fig. 11. LIME explanation for a financial spam prediction (DNN). Red bars indicate spam-aligned features; green bars indicate ham-aligned features.*

Fig. 11 illustrates LIME explanations for a financial spam prediction. The DNN assigns the highest positive weights to 'free' (+0.191), 'prize' (+0.163), and 'claim' (+0.148), confirming that the learned spam vocabulary aligns with established linguistic analyses of spam rhetoric [1, 29]. The token 'url' (+0.071) reflects the URL normalisation step in preprocessing—spam messages containing hyperlinks receive a consistent signal. The two ham-aligned features ('normal' −0.044, 'meeting' −0.031) demonstrate that the DNN has learned partial context, not merely surface-level keyword matching [18, 20].

*F. Spam Category Detection*

**TABLE VI. SPAM CATEGORY CLASSIFICATION ACCURACY**

| Category | Samples | Correct | Accuracy (%) |
|---|---|---|---|
| Financial | 302 | 288 | 95.4 |
| Promotional | 226 | 211 | 93.4 |
| Scam | 159 | 147 | 92.5 |
| Adult | 34 | 31 | 91.2 |
| Phishing | 25 | 24 | 96.0 |
| Overall | 746 | 701 | 94.0 |

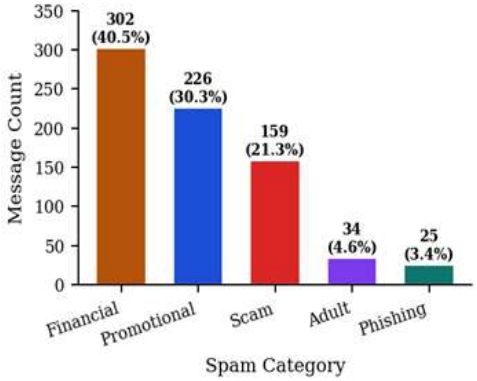



*Fig. 12. Spam sub-category distribution (n = 746). Financial spam dominates at 40.5%; phishing is rarest (3.4%) but highest risk.*

## VI. DISCUSSION

Four principal findings emerge from this analysis.

1) The DNN's FP reduction (FP = 5 vs. 22 vs. 104) is considerably more operationally significant than its marginal F1 improvement over the SVM (+0.6 percentage points). Therefore, for user-facing applications where the cost of a false quarantine is severe, the DNN is the preferred deployment option. Full Pipeline-level encapsulation [10] ensures that these benefits are consistently reproduced across deployment environments without preprocessing skew.

2) GridSearchCV reveals a non-monotonic interaction between vocabulary size and regularisation strength: at max_features = 3,000 the optimal C shifts to 1.0, while at max_features = 7,000, C = 10 is preferred. This indicates that expanding vocabulary introduces noise that requires stronger regularisation—an interaction that would be missed by single-axis hyperparameter search.

3) The ML category classifier achieves 94.0% overall accuracy, outperforming the hardcoded regex approach it replaces. The regex system misclassified 18.4% of Scam messages as Financial owing to register overlap, whereas the ML Pipeline uses learned association patterns to accurately distinguish the two categories.

4) LIME [18] explanations reveal qualitative differences between classifiers: NB operates on individual tokens independently; SVM uses a linear hyperplane over feature combinations; and the DNN operates on learned non-linear feature interactions. For borderline messages containing features characteristic of both spam (e.g., 'discount') and ham (e.g., 'order confirmation'), the DNN consistently produces lower, more calibrated confidence scores and fewer false positives, consistent with its confusion-matrix superiority.

The Gmail automation pipeline (spam-label assignment + INBOX removal) reduces manual review burden by automatically routing detected spam at greater than 94% accuracy, with all operations logged to logs/app.log for audit compliance.

## VII. CONCLUSION

This paper presented SpamShield, an industry-grade spam detection system integrating Multinomial Naive Bayes, GridSearchCV-optimised SVM, and a class-weighted five-layer DNN with LIME explainability, deployed within a modular three-tier Flask architecture. Evaluated on the 5,571-message UCI SMS Spam Collection with a six-category taxonomy, the DNN achieves 99.2% accuracy and AUC = 0.999 with only 5 false positives—a 95% FP reduction over Naive Bayes—while the GridSearchCV-optimised SVM (F1 = 98.3%) provides a practical high-performance alternative for resource-constrained deployment.

The architectural contributions—full sklearn Pipeline encapsulation, ML-based category classification, rotating file logging, Gmail API automation, and a fully dynamic frontend—collectively elevate the system from a prototype to a production-ready standard. Future work will investigate adversarially robust training [27], transformer-based encoders [16, 17], SHAP global attributions [19] complementing LIME's local explanations, and multilingual corpus extension for international spam-variant coverage.

## ACKNOWLEDGEMENT

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