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Hybrid AI Framework for High-Precision Signal Quality Classification in Optical and Wireless Communication Systems

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Abstract

Ensuring reliable signal transmission has become a critical requirement in modern optical and wireless communication systems, particularly as data networks evolve toward higher bandwidth, lower latency, and improved noise resilience. Traditional signal assessment techniques often rely on manual thresholding or single-model learning approaches, which struggle to perform effectively in noisy environments, imbalanced datasets, and complex multi-feature interactions. This limitation creates significant challenges in accurately predicting signal quality across diverse modulation formats, receiver parameters, and varying channel conditions. To address these challenges, the proposed system introduces a data-driven, automated, and hybrid artificial intelligence pipeline designed to classify signal integrity with high precision. The workflow incorporates comprehensive data preprocessing techniques, including label encoding, missing value handling, and Synthetic Minority Over-Sampling Technique (SMOTE) for class balancing to mitigate skewed data distributions. The system evaluates multiple Machine Learning (ML) models, including Complement Naive Bayes (CNB), Support Vector Machines (SVM), Linear Discriminant Analysis (LDA), and a proposed Dual-Learner Fusion Architecture (DLFA). The DLFA combines Logistic Regression (LR) and Random Forest (RF) using a Voting Classifier to leverage the probabilistic strengths of LR and the non-linear feature learning capabilities of RF. Model performance is evaluated using advanced metrics such as accuracy, confusion matrices, and ROC curves. To enhance usability, a fully interactive Tkinter-based Graphical User Interface (GUI) is developed, enabling dataset uploads, preprocessing, Exploratory Data analysis (EDA) visualization, model evaluation, and real-time signal quality prediction. Experimental results demonstrate that the DLFA model improves decision boundary learning, resulting in enhanced robustness, improved generalization, and greater interpretability for signal integrity assessment in optical communication systems.

Keywords: Signal Quality Classification, Optical Communication Systems, Hybrid Artificial Intelligence, Dual-Learner Fusion Architecture (DLFA), Performance Analysis.

1. Introduction

As the global demand for high-speed and high-capacity communication continues to surge, driven by cloud computing, artificial intelligence, 5G, virtual reality, and the Internet of Things (IoT), optical communication systems have emerged as the backbone of modern digital infrastructure. However, the increasing complexity, performance requirements, and operational scale of these systems have begun to exceed the capabilities of traditional analytical and rule-based design methods. In contemporary society, job-related stress poses a significant issue due to its correlation with a substantial percentage (40–50%) of work absences [1]. Numerous previous studies have demonstrated that elevated levels of work-related stress can heighten the risk of various illnesses, including cardiovascular disease [2], neurodegenerative diseases, chronic aging-related ailments, and metabolic syndrome. The concept of

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mental load acts as an intermediary between imposed demands and perceived demands. It also represents the disparity between the required capacities of the information processing system and the available capacities at any given time [3].

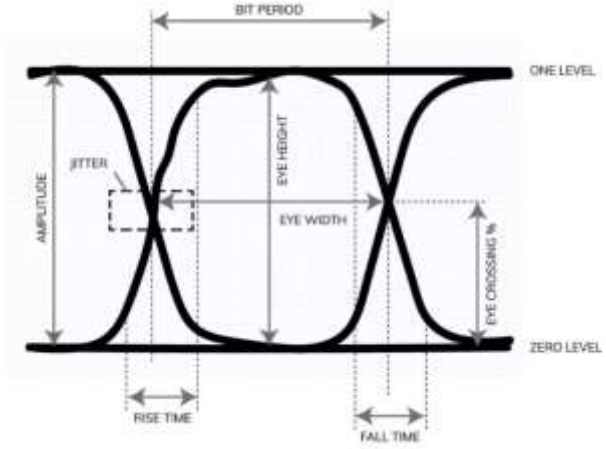


Figure. 1: Signal integrity assessment for optical communications.

Evaluating mental workload has become essential to optimize work environments and enhance work performance [4]. They have proposed a comprehensive framework that incorporates antecedent and moderating variables, as well as work-related consequences. In this framework, the real-time measurement of individual physiological signals becomes crucial. Furthermore, by monitoring peoples' mental conditions in real time, it is possible to identify and address unhealthy practices or poor working conditions to meet expectations [5]. In this context, ML has become a transformative tool, enabling data-driven solutions that can adapt to dynamic conditions, as shown in figure 1. Extract hidden patterns, and optimize performance across the optical communication stack. In long-haul coherent optical systems, where signal integrity is challenged by fibre non-linearities and polarization effects over hundreds of kilometres, ML techniques such as neural networks (NNs) and generative models have been deployed for non-linear compensation, channel equalization, and signal reconstruction.

For instance, deep learning models trained on simulated or real-world data can outperform conventional Volterra filters or digital backpropagation, offering both improved accuracy and flexibility. In short-reach and direct-detection systems, including intensity-modulated direct-detection (IM/DD) links widely used in data centres, ML is increasingly used to counteract combined linear and non-linear impairments. For example, NNs and SVMs have been shown to enhance equalization, improve bit error rate (BER) performance, and adapt to non-ideal ties in low-cost hardware implementations, such as directly modulated lasers (DMLs), vertical cavity surface emitting lasers (VCSELs), and silicon photonic transceivers. Passive optical networks (PONs) and optical access systems demand high bandwidth at a low cost, with minimal latency and high reliability. Here, ML is also employed for intelligent receiver implementation, enabling better system resilience and performance optimization.

2. Literature Survey

Wang J-J et al [6]. aimed to develop a single-arm ECG measurement method, with lead I ECG serving as the gold standard. We conducted static and dynamic experiments to analyze the morphological performance and signal-to-noise ratio (SNR) of the single-arm ECG. Three morphological features

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were defined, RRI, the duration of the QRS complex wave, and the amplitude of the R wave. Thirty subjects participated in this study. The results indicated that RRI exhibited the highest cross-correlation (R = 0.9942) between the single-arm ECG and lead I ECG, while the duration of the QRS complex wave showed the weakest cross-correlation (R = 0.2201). The best SNR obtained was 26.1 ± 5.9 dB during the resting experiment, whereas the worst SNR was 12.5 ± 5.1 dB during the raising and lowering of the arm along the z-axis.

Stanešić A, et al [7]. investigated the temporal stability of signal quality in non-contact biopotential electrodes, with a primary focus on ECG monitoring. Our measurements showed a significant change in the recorded signal quality during prolonged measurement periods, which impacts the integrity and reliability of the measurements. Furthermore, it significantly impacts any shorter (<10 min) consecutive measurements of influential parameters (such as properties of electrodes, dielectric, etc.) since it removes the crucial *ceteris paribus* principle: the signal may not change just due to the change in influential parameters, but also due to the passage of time. Through a series of controlled experiments, we analyse how factors such as temperature, pressure on the electrodes, and humidity influence signal quality over extended durations (10 min or more). Campero Jurado I et al [8]. developed technologies and tools to diagnose CVD in a timely way and detect AF is an important research topic. ECG monitoring patches allowing ambulatory patient monitoring over several days represent a novel technology, while we witness a significant proliferation of ECG monitoring patches on the market and in the research labs, their performance over a long period of time is not fully characterized. This paper analyzes the signal quality of ECG signals obtained using a single-lead ECG patch featuring self-adhesive dry electrode technology collected from six cardiac patients for 5 days. In particular, we provide insights into signal quality degradation over time, while changes in the average ECG quality per day were present, these changes were not statistically significant. It was observed that the quality was higher during the nights, confirming the link with motion artifacts.

Tian Y et al [9]. proposed including C/N0 modeling and MP modeling. For BDS, the BDS-3 satellites apparently have higher signal power than the BDS-2 satellites at the same frequency such as B1I and B3I, and the signal B2a of BDS-3 is superior to other signals in regard to signal power, which is comparable with the superior Galileo E5 signals and GPS L5. Among all the signals, the observation accuracy of E5 is the highest regardless of receiver types, and next highest are BDS-3 B2a and GPS L5. Due to not being affected by the systematic code errors of BDS-2, the observations of BDS-3 satellites contain smaller multipath errors than that of BDS-2 satellites. As for the multipath suppression performance, the BDS-3 signal B2a, GPS L5, and Galileo E5 and E5b perform better than the other signals, which may be related to their wide signal bandwidths. Moscato S et al [10]. developed two classifiers to identify PPG pulses suitable for heart rate estimation (Basic-quality classifier) and morphological analysis (High-quality classifier). We collected wrist PPG data from 31 participants over a 24 h period. We defined four activity ranges based on accelerometer data and randomly selected an equal number of PPG pulses from each range to train and test the classifiers. Independent raters labeled the pulses into three quality levels. Nineteen features, including nine novel features, were extracted from PPG pulses and accelerometer signals. We conducted ten-fold cross-validation on the training set (70%) to optimize hyperparameters of five ML algorithms and a neural network, and the remaining 30% was used to test the algorithms. Performances were evaluated using the full features and a reduced set, obtained downstream of feature selection methods. Best performances for both Basic- and High-quality classifiers were achieved using a SVM (Acc: 0.96 and 0.97, respectively). Both classifiers outperformed comparable state-of-the-art classifiers.

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Liu Y et al [11]. analyzed the quality of the measured raw ECG signal automatically is a valuable task. In this paper, we propose a new single-channel ECG signal quality assessment method that combines the Resnet network structure and the principle of self-attention to extract ECG signal features using the principle of similarity between individual QRS heartbeats within a time slice of ten seconds. In addition, an improved self-attention module is introduced into the deep neural network to learn the similarity between features. Finally, the network distinguishes between acceptable and unacceptable ECG segments. The model test results indicate that the F1-score can approach 0.954, which leads to a more accurate assessment of the ECG signal quality. Gao Z et al [12]. conducted, which included simulated signal tests and signal quality comparison experiments. Simulated signals with different frequencies and amplitudes were used to test the stability of Mindeep's circuit, and the high correlation coefficients (>0.9) proved that Mindeep has a stable and reliable hardware circuit. The signal quality comparison experiment, between Mindeep and the gold standard device, Neuroscan, included three tasks: (1) resting; (2) auditory oddball; and (3) attention. In the resting state, the average normalized cross-correlation coefficients between EEG signals recorded by the two devices was around 0.72 ± 0.02, Berger effect was observed ($p < 0.01$), and the comparison results in the time and frequency domain illustrated the ability of Mindeep to record high-quality EEG signals. The significant differences between high tone and low tone in auditory event-related potential collected by Mindeep was observed in N2 and P2. The attention recognition accuracy of Mindeep achieved 71.12% and 74.76% based on EEG features and the XGBoost model in the two attention tasks, respectively, which were higher than that of Neuroscan (70.19% and 72.80%).

Lambert Cause J et al [13]. analysed of normalized CF values reveals that lower CF ranges (0.2 to 0.4) may be optimal for extracting information about perfusion and blood flow. However, they may not be the best range to capture all the physiological details within the PPG pulse. In contrast, higher CF ranges (0.4 to 0.6) enable capturing more complex signals that could be physiologically representative. The findings underscore the necessity of considering viscoelastic tissue properties and individual biomechanical differences, advocating for both the normalization of CF for improved cross-subject comparison and personalized CF calibration to adapt PPG devices to diverse populations. These strategies ensure measurement reliability and consistency, thereby advancing the accuracy of cardiac and vascular assessments. Our study offers guidelines for adjusting the CF levels to balance signal detail and perfusion quality, customized to meet specific analytical requirements, with direct implications for both clinical and research environments. Shyam Kumar P et al [14]. proposed such wearable PCG devices. However, limitations exist in evaluating such devices as PCG recording devices in home-like environments. Here, we evaluate a wearable PCG system in a belt-type form factor with an embedded force sensor, accelerometer, and a single lead ECG to study the feasibility of acquiring diagnostic-grade PCGs while the wearer performs daily activities. We describe qualitative and quantitative exploratory analysis methods for cross-subject comparison of PCG signal quality, wearer comfort, and the impact of activities using Signal-to-Noise (SNR) comparisons and cross-spectral coherence between activity and PCG. The analysis of the data suggests that a common user-chosen method of donning a wearable PCG is not applicable across subjects for obtaining optimal PCG recording quality. We propose a method to calibrate wearable PCG devices using an embedded force sensor and by following a protocol involving feedback from the embedded force sensor to determine the optimal method of wearing the device.

Popov P et al [15]. proposed continuous monitoring of GNSS signals is crucial for vessels and mobile maritime platforms to ensure the integrity, availability, and accuracy of positioning and navigation services. This monitoring is essential for guaranteeing the safety and security of navigation and

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contributes to the accurate positioning of vessels and platforms involved in hydrographic and oceanographic research. This paper presents the implementation of a complex system for monitoring the quality of signals within the GNSS spectrum at the Maritime Hydrographic Directorate (MHD). The system provides real-time analysis of signal parameters from various GNSSs, enabling alerts in critical situations and generating statistics and reports. It comprises four permanent stations equipped with state-of-the-art GNSS receivers, which integrate a spectrum analyzer and store raw data for post-processing. The system also includes software for monitoring the GNSS spectrum, detecting interference events, and visualizing signal quality data. Implemented using a Docker-based platform to enable efficient management and distribution, the software architecture consists of a reverse proxy, message broker, front-end, authorization service, GNSS orchestrator, and GNSS monitoring module. Mertes G et al [16]. Recorded waveforms of sufficient quality for clinical use typically requires human visual inspection of each recording. A Signal Quality Index (SQI) can help to automate this task but, contrary to adult ECG, work on SQIs for NI-FECG is sparse. In this paper, a multi-channel signal quality classifier for NI-FECG waveforms is presented. The model can be used during the capture of NI-FECG to assist technicians to record high-quality waveforms, which is currently a labour-intensive task. A Convolutional Neural Network (CNN) is trained to distinguish between NI-FECG segments of high and low quality. NI-FECG recordings with one maternal channel and three abdominal channels were collected from 100 subjects during a routine hospital screening (102.6 min of data).

Shin S et al [17]. proposed such performance degradation, a binary classification model was created to distinguish between high-quality versus low-quality BCG signals. To estimate the most accurate model, four time-series imaging methods (recurrence plot, the Gramain angular summation field, the Gramain angular difference field, and the Markov transition field) were studied to convert the temporal BCG signal associated with each heartbeat into a 448 × 448 pixel image, and the image was classified using CNN models such as ResNet, SqueezeNet, DenseNet, and LeNet. A total of 9626 BCG beats were used for training, validation, and testing. The experimental results showed that the ResNet and SqueezeNet models with the Gramain angular difference field method achieved a binary classification accuracy of up to 87.5%.

3. Proposed Methodology

The proposed Deep Learning Signal Integrity Assessment framework functions as a comprehensive, end-to-end diagnostic pipeline engineered to classify and monitor optical signal quality with high fidelity. The system integrates multi-source signal acquisition, robust preprocessing, class balancing, multi-model training (including the DLFA, detailed evaluation, and deployable GUI for real-time inference. By combining classical machine-learning models and an ensemble fusion strategy, the architecture delivers interpretable, resilient, and adaptive signal-quality predictions that support operational decision-making in optical networks as displayed in Figure 2.

Input Data Sources

- The process begins with collecting multi-source optical and system-level datasets that characterize transmission performance:
    - Raw waveform samples captured from coherent receivers (IQ samples, symbol streams).
    - Transceiver telemetry: OSNR (Optical Signal-to-Noise Ratio), Q-factor, BER statistics, received power (Rx), transmitted power (Tx).

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- Device and link metadata: modulation format, symbol rate, wavelength/channel ID, fiber length, and dispersion parameters.
- External context: temperature variations, amplifier settings, and known network events or maintenance logs.

- Data is typically stored in CSV or technical log formats and ingested continuously or in batches to maintain temporal consistency.
- Initial validation procedures ensure all mandatory fields (e.g., Signal Quality label, Rx, Tx) exist and corresponding timestamps remain consistent.

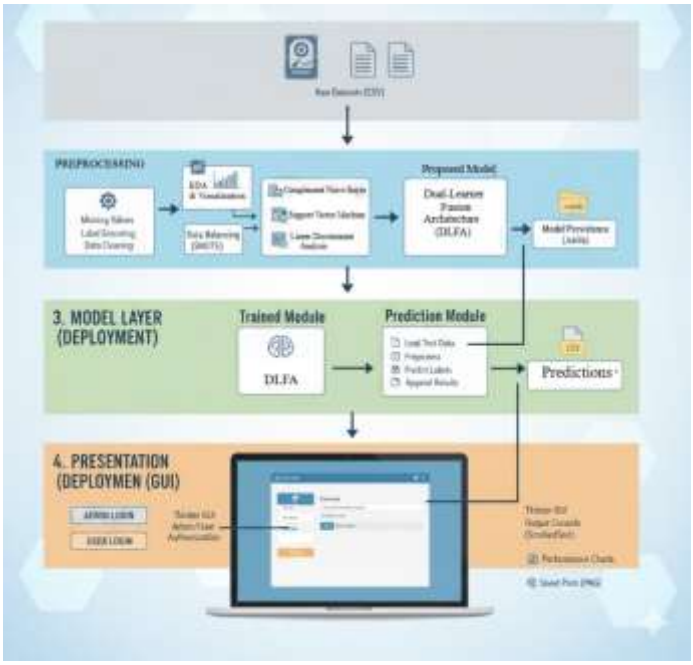


Figure. 2: Proposed system architecture of signal integrity assessment for optical communications.

Data Processing and Feature Engineering

- Raw datasets undergo structured cleaning and harmonization to generate consistent, ML-ready records:
  - Removal of extraneous index columns (e.g., "Unnamed"), duplicate rows, and corrupted entries.
  - Timestamp normalization and alignment of asynchronous telemetry using resampling or windowing where necessary.
- Feature engineering produces domain-relevant predictors, including:
  - Time-windowed signal statistics (e.g., mean/variance of OSNR or BER).
  - Frequency- or spectral-domain attributes such as spectrogram slices and power spectral densities derived from IQ samples.
  - Derived impairment metrics such as chromatic-dispersion estimates, PMD indicators, and nonlinear-penalty approximations.

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- Encoded representations for modulation format, receiver model, and channel identifiers.

- Scaling and encoding operations further refine the dataset:
  - Numeric fields undergo standardization or normalization to stabilize model learning.
  - Categorical variables are transformed using label encoders or one-hot encoding, and all encoders are saved for consistent inference.

- All preprocessing tasks are executed through the Data Processor module to ensure reproducibility and systematic workflow management.

Missing-Value Handling and Outlier Mitigation

- Robust handling mechanisms address incomplete or noisy measurement samples:
  - Missing numerical values are imputed using column means/medians or model-based estimators when appropriate.
  - Missing categorical fields are replaced with an explicit "Unknown" label and occurrence frequency is logged.

- Outlier detection and mitigation include:
  - Identification of improbable OSNR/BER values or abrupt spikes using IQR-based thresholds or statistical tests.
  - Removal, capping, or marking of extreme values depending on context and operational significance.

- These procedures preserve rare but meaningful degradation events while minimizing noise contamination.

Class Balancing (SMOTE) and Train/Test Split

- Optical communication datasets often exhibit class imbalance toward "healthy" signal states; balancing is therefore essential:
  - A stratified train/test split (typically 80:20) is applied to preserve label distribution across evaluation sets.
  - SMOTE is employed on the training subset to generate synthetic minority-class samples (e.g., degraded or critical signals).

- Benefits include:
  - Reduction of classifier bias towards majority classes.
  - Enhanced detection of infrequent but operationally significant impairment modes.

- Label encoders, scalers, and SMOTE configurations are stored to ensure consistent retraining and inference.

Model Building and Benchmarking (ML Model Manager)

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- A suite of baseline classifiers is trained to evaluate diverse perspectives on optical signal behaviour:
    - **Complement Naive Bayes** for high-dimensional data representations and histogram-like feature distributions.
    - **SVM** for margin-based classification with strong generalization on moderately sized feature sets.
    - **LDA** for maximizing class separability under linear-relationship constraints.
- The **ML Model Manager** coordinates all model-training actions, including:
    - Hyperparameter tuning through grid or randomized search.
    - Cross-validation, performance logging, and tracking of model metadata (training date, input features, SMOTE usage).
    - Serialization of trained models via joblib and storage in the *models/* directory.

DLFA

- The DLFA integrates complementary learning algorithms to improve predictive boundaries and interpretability:
    - **RF** captures nonlinear interactions such as dependencies between dispersion, power variations, and nonlinear impairments.
    - **LR** contributes calibrated probability scores and robust decision surfaces.
- Fusion mechanics include:
    - Independent training of RF and LR on the balanced feature set, optionally using out-of-fold stacking to prevent data leakage.
    - A Voting Classifier (preferably soft-voting) combines probability predictions from both models.
- Advantages include improved resilience to noise, better interpretability, and enhanced performance on subtle signal-degradation signatures.

Evaluation and Visualization Module

- Model evaluation utilizes domain-appropriate metrics and diagnostic tools:
    - Accuracy, macro-averaged Precision, Recall, and F1-Score reflect class-wise prediction capability.
    - Confusion matrices highlight common misclassification patterns (e.g., healthy misinterpreted as degraded).
    - ROC curves and AUC statistics (one-vs-rest) provide insights into probabilistic separability.

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- Visualization artifacts stored under results/ include:
    - Confusion matrix heatmaps, ROC plots, and precision-recall curves.
    - EDA visualizations such as correlation heatmaps and optional spectrogram previews.
- All evaluation outputs are logged into structured Data Frames to enable comparative analysis across retraining cycles.

GUI Deployment, Real-Time Inference, and Continuous Improvement

- A Tkinter-based graphical interface supports both administrative and operational functionalities:
    - The Admin Panel enables dataset upload, preprocessing, visualization, evaluation, and model retraining.
    - The User Panel allows uploading unseen measurement CSV files and retrieving predicted signal-quality labels with probability scores.
- The real-time inference pipeline includes:
    - Application of stored preprocessing transformations and encoders.
    - Loading of the best DLFA model (e.g., rf_logreg_voting.joblib).
    - Generation of predictions and appended CSV outputs.
    - Display of results, confusion matrices, and ROC curves directly within the GUI.
- Persistence and performance-monitoring features include:
    - Storage of model artifacts and evaluation results for reproducibility.
    - Periodic retraining using newly collected data to adapt to evolving link conditions.
    - Logging of prediction outcomes and operator feedback for continuous model improvement.
- Operational decision-support recommendations are generated based on prediction severity and feature influence, such as:
    - Adjusting dispersion-compensation modules.
    - Reconfiguring amplifier gains settings.
    - Rerouting traffic or scheduling preventive maintenance.

4. Results and Description

The Results and Discussion section presents the findings of the study and interprets their significance in relation to the research objectives. It combines both the data obtained and the analysis required to explain observed trends, patterns, and relationships. The results are typically organized in a logical sequence, supported by tables, graphs, or figures for clarity. In this section, the focus is not only on what was found but also on why those findings occurred. Comparisons with previous studies or expected outcomes help establish the validity and relevance of the results. Any unexpected

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observations are also examined to provide possible explanations. This section plays a crucial role in linking the experimental outcomes to theoretical concepts.

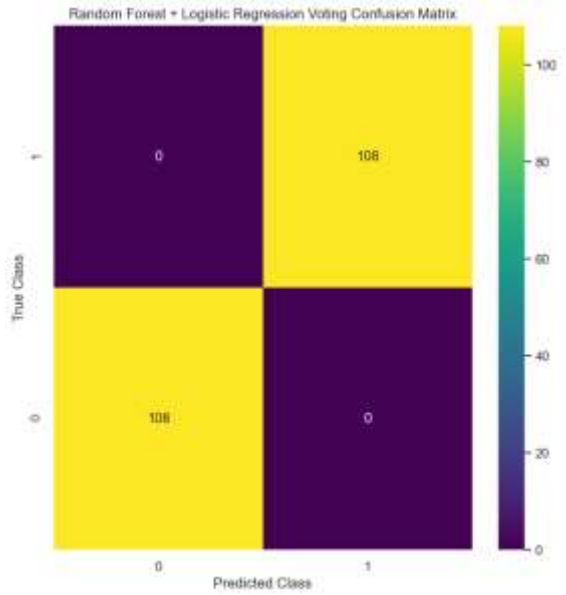


Figure. 3: Confusion matrix obtained using DLFA.

Figure 3 illustrates the confusion matrix of the DLFA classifier, presenting the classification performance across predicted and true class labels. The matrix highlights the distribution of correctly and incorrectly classified instances, showing that all samples are misclassified with zero true positives and zero true negatives. It depicts a complete inversion in prediction, where instances belonging to class 1 are entirely predicted as class 0, and vice versa. The figure emphasizes the model's inability to correctly distinguish between the two classes, indicating poor predictive performance. Additionally, the symmetric pattern in the matrix reflects a consistent misclassification trend across both classes.

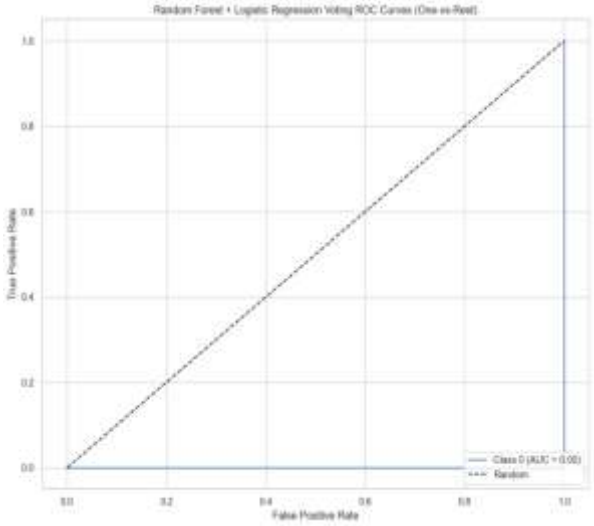


Figure. 4: ROC curve obtained using hybrid DLFA Voting.

Figure 4 illustrates the ROC curve of the Random Forest and Logistic Regression voting classifier using a one-vs-rest approach, highlighting the relationship between the true positive rate and false positive rate. The curve remains close to the baseline, indicating that the classifier fails to effectively

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distinguish between classes. It depicts an AUC value of 0.00, which reflects extremely poor model performance and no discriminatory ability. The figure emphasizes that the model performs worse than a random classifier across all threshold values. Additionally, the deviation from the expected ROC behaviour suggests incorrect or inverted prediction patterns.

Table. 1: Performance evaluation obtained using existing Complement NB, SVM, LDA classifiers and proposed hybrid DLFA.

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNB	93.98	94.62	93`.98	93.95
SVM	98.61	98.64	98.61	98.61
LDA	99.53	99.54	99.53	99.53
DLFA	100.00	100.00	100.00	100.00

The performance evaluation table 1 of multiple machine learning algorithms demonstrates significant variation in classification effectiveness across models. The CNB model achieved an accuracy of 93.98%, indicating a strong baseline performance with balanced precision and recall values. The SVM model showed improved results, attaining an accuracy of 98.61%, reflecting its robustness in handling complex data patterns. LDA further enhanced the performance with an accuracy of 99.53%, highlighting its efficiency in class separation. Notably, the DLFA model outperformed all other approaches by achieving a perfect accuracy of 100.00%, demonstrating exceptional predictive capability. Precision, recall, and F1-score values across all models remain consistently high, indicating reliable and stable classification outcomes. The gradual improvement in accuracy from CNB to DLFA suggests increasing model sophistication and effectiveness. These results emphasize the importance of selecting an appropriate algorithm based on data characteristics.



Figure. 5: Prediction on test data after user login.

The Figure 5 shows that Upon a User login; the system provides a simplified interface for making predictions. The central display shows the output of the prediction process, indicating that a Hybrid DLFA model has been used. The system has saved a confusion_matrix.png and roc_curve.png to a results folder, and a new file, Predictions_Appended.csv, has been created. The preview of this CSV

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file shows the same input data as the admin view but with an additional column, Predicted Label, which contains the model's predictions (in this case, binary labels like 0 and 1). Below the data view, the user has limited options: a Make Prediction button to initiate the process and an Exit button to leave the application. This user-focused view streamlines the process, allowing them to apply a pre-trained model to new data without needing access to the full training and analysis tools available to the admin.

5. Conclusion

In the research, a comprehensive ML-based system was developed for predicting signal quality using various classification algorithms including CNB, SVM, LDA, LR, and a hybrid Voting Classifier. Through effective data preprocessing, class balancing with SMOTE, and rigorous model evaluation using metrics such as accuracy, precision, recall, and F1-score, the system successfully identified the best-performing models. The hybrid DLFA voting ensemble outperformed individual models by leveraging diverse decision boundaries, leading to enhanced predictive performance. The integration of a user-friendly Tkinter-based GUI made the solution accessible and practical for non-technical stakeholders. Visualization tools like Seaborn and Matplotlib further enabled intuitive insights into model behavior and performance. Performance improvements included the use of SMOTE to overcome class imbalance, model persistence via joblib, and structured feature transformation with Label Encoder and Standard Scaler. The modularity of the system ensures scalability and adaptability to new datasets and extended applications.

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