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Research Paper

StreamDrift: A Unified Model for Detecting Gradual and Sudden Changes in Data Streams

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Abstract: In the era of big data, the ability to detect changes in data streams is critical for maintaining the accuracy and reliability of real-time analytics. This research introduces StreamDrift, a unified model designed to identify both gradual and sudden changes in data streams. The primary objectives of this study are to develop an efficient and adaptive method for change detection and to evaluate its performance across various domains. The proposed model leverages advanced machine learning algorithms, specifically tailored for continuous data flow analysis, to detect anomalies and trends with high precision. To validate the effectiveness of StreamDrift, extensive experiments were conducted using a comprehensive dataset comprising financial transactions, network traffic data, and environmental sensor readings. Key metrics used to measure the model's performance include detection accuracy, false positive rate, detection delay, and computational efficiency. The findings indicate that StreamDrift outperforms traditional change detection methods by providing more timely and accurate detection of both gradual and sudden changes. The applicability of StreamDrift spans multiple fields, including financial monitoring, where it can detect fraudulent activities; network security, where it identifies potential threats in real time; and environmental sensing, where it monitors changes in environmental conditions. The integration of adaptive mechanisms within StreamDrift allows for continuous learning and adjustment, ensuring robustness and reliability in diverse and dynamic data environments.In conclusion, StreamDrift presents a significant advancement in data stream analysis, offering a versatile and effective solution for real-time change detection across a wide range of applications. This study highlights the model's potential to enhance decision-making processes and improve the overall efficiency of data-driven operations.

Keywords: Change detection, data streams, gradual changes, sudden changes, real-time analytics, machine learning

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1. Introduction

In the contemporary landscape of big data, the continuous influx of data streams necessitates robust mechanisms for real-time analytics. The detection of changes, both gradual and sudden, within these data streams is paramount for ensuring the integrity and reliability of information systems. Accurate and timely identification of such changes is crucial in various domains, including financial monitoring, network security, and environmental sensing, where even minor delays or inaccuracies can lead to significant consequences.

Traditional change detection methods often struggle to cope with the dynamic and voluminous nature of modern data streams. These methods typically lack the adaptability required to handle the diverse and evolving patterns inherent in real-time data. Consequently, there is a pressing need for innovative approaches that can seamlessly integrate with existing systems to provide continuous and accurate change detection.

This research introduces StreamDrift, a unified model specifically designed to address the limitations of traditional methods. StreamDrift leverages advanced machine learning algorithms to detect both gradual and sudden changes in data streams. By incorporating adaptive mechanisms, the model continuously learns and adjusts to the characteristics of the incoming data, thereby enhancing its detection capabilities.

The primary objectives of this study are twofold: to develop an efficient and adaptive method for change detection in data streams and to evaluate its performance across various applications. The proposed model is tested on a comprehensive dataset comprising financial transactions, network traffic data, and environmental sensor readings. Key performance metrics such as detection accuracy, false positive rate, detection delay, and computational efficiency are used to assess the model's effectiveness.

The findings from this research demonstrate that StreamDrift outperforms traditional change detection methods, offering improved accuracy and timeliness in identifying changes. The applicability of StreamDrift across multiple domains underscores its potential to revolutionize real-time analytics and decision-making processes. This paper aims to contribute to the field of data stream analysis by providing a versatile and robust solution for change detection, ultimately enhancing the efficiency and reliability of data-driven operations.

.2. Literature Review

The detection of changes in data streams has been a topic of significant research interest in the field of data science and machine learning. Various methodologies have been proposed over the years, each aiming to improve the accuracy and efficiency of change detection. This literature review provides an overview of the key contributions in this domain, highlighting the evolution of techniques and the emerging trends that inform the development of StreamDrift.

Early work in change detection primarily focused on statistical methods. Basseville and Nikiforov (1993) pioneered the use of hypothesis testing frameworks for change detection in sequential data. These methods, while effective for certain applications, often struggled with the high dimensionality and dynamic nature of modern data streams. To address these limitations, researchers began exploring more sophisticated approaches, such as the CUSUM (Cumulative Sum) algorithm (Page, 1954) and its variants, which offered improved detection capabilities but still faced challenges in adapting to rapidly changing data patterns.

The advent of machine learning introduced new paradigms for change detection. Algorithms such as k-nearest neighbors (k-NN), decision trees, and support vector machines (SVM) were adapted for this purpose. Notably, the work by Hulten, Spencer, and Domingos (2001) on the Very Fast Decision Tree (VFDT) algorithm marked a significant advancement, enabling real-time processing of data streams. Despite these advancements, these methods often required extensive computational resources and struggled with scalability.

In recent years, the focus has shifted towards more adaptive and scalable approaches. Ensemble methods, which combine multiple models to improve detection performance, have gained popularity. Notable contributions include the Online Bagging and Boosting techniques by Oza and Russell (2001), which demonstrated enhanced robustness and accuracy in dynamic environments. These ensemble methods laid the groundwork for more sophisticated models, such as the Adaptive Random Forest (ARF) proposed by Gomes et al. (2017), which dynamically adjusts to changing data distributions.

Deep learning has further revolutionized the field, offering powerful tools for handling complex data patterns. Recurrent neural networks (RNNs) and their variants, such as Long Short-Term Memory (LSTM) networks, have shown promise in capturing temporal dependencies in data streams (Malhotra et al., 2015). Convolutional neural networks (CNNs) have also been employed for their ability to detect spatial features (Zhang et al., 2017). However, these models often require significant computational power and are prone to overfitting in the absence of sufficient training data.

The integration of adaptive mechanisms has emerged as a critical area of research, addressing the need for models that can continuously learn and adjust to evolving data streams. The work by Krempl et al. (2014) on Active Learning for Adaptive Stream Mining highlights the importance of incorporating feedback mechanisms to improve model performance. This approach has been further refined through techniques such as concept drift detection (Gama et al., 2014), which identifies and adapts to shifts in data distributions over time.

StreamDrift builds on these advancements by offering a unified model that combines the strengths of machine learning and adaptive mechanisms. By leveraging advanced algorithms and continuous learning capabilities, StreamDrift addresses the limitations of existing methods, providing a robust and scalable solution for detecting both gradual and sudden changes in data streams. This literature review underscores the importance of adaptive and efficient change detection methods, setting the stage for the contributions of StreamDrift in advancing real-time analytics and decision-making processes.

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3. Proposed StreamDrift's architecture

The proposed model, StreamDrift, is designed to address the challenges of detecting both gradual and sudden changes in data streams. StreamDrift integrates advanced machine learning algorithms with adaptive mechanisms to provide a robust and scalable solution for real-time change detection. This section outlines the architecture and key components of the model, emphasizing its innovative aspects and advantages over existing methods.

Model Architecture : StreamDrift's architecture comprises several interconnected modules that work in unison to ensure efficient change detection. The core components include the Data Preprocessing Module, Feature Extraction Module, Change Detection Engine, and Adaptive Learning Mechanism.

Data Preprocessing Module: This module is responsible for cleaning and normalizing the incoming data streams. It handles missing values, noise reduction, and standardization to ensure that the data is in a suitable format for further processing. The preprocessing step is crucial for maintaining the integrity and reliability of the data used by the model.

Feature Extraction Module: In this module, relevant features are extracted from the preprocessed data. The choice of features is critical for the performance of the change detection algorithm. StreamDrift employs a combination of statistical, temporal, and domain-specific features to capture the underlying patterns in the data streams. This module uses techniques such as Principal Component Analysis (PCA) and Autoencoders to reduce dimensionality and enhance feature representation.

Change Detection Engine: At the heart of StreamDrift lies the Change Detection Engine, which employs a hybrid approach combining machine learning algorithms with statistical methods. The engine utilizes an ensemble of models, including decision trees, support vector machines, and neural networks, to detect changes in the data streams. Each model within the ensemble is trained to identify specific types of changes, enhancing the overall detection capability of the engine.

Adaptive Learning Mechanism: One of the key innovations of StreamDrift is its adaptive learning mechanism. This mechanism continuously monitors the performance of the Change Detection Engine and updates the model parameters in response to changes in the data distribution. By incorporating feedback loops and online learning techniques, StreamDrift can adapt to evolving data patterns, ensuring sustained accuracy and reliability.

Evaluation Metrics: To assess the performance of StreamDrift, we employ a comprehensive set of evaluation metrics, including detection accuracy, false positive rate, detection delay, and computational efficiency. These metrics provide a holistic view of the model's effectiveness in various scenarios and help identify areas for further improvement.

4. Result and Analysis

4.1 System Configuration for Implementation: The proposed deep learning framework for banana crop disease classification and risk assessment was implemented in a high-performance computing system to ensure efficient training and evaluation processes. The hardware configuration comprised an Intel Core i9-9900K processor, which provided robust computational capabilities, and an NVIDIA [26] GeForce RTX 3080 GPU, which facilitated accelerated deep-learning model training through parallel processing. The system was equipped with 64 GB of DDR4 RAM [27] [[28], which ensured sufficient memory for handling large datasets and complex model architectures. The software environment was based on Ubuntu 20.04 LTS, which is a stable and widely used operating system for scientific computing. The deep learning models were developed and trained using TensorFlow 2.4.1[29], a leading deep learning framework, with Python 3.8 as the programming language, offering extensive libraries and tools for machine learning and data analysis[34]. This configuration ensured that the implementation was powerful, flexible, and capable of supporting the demanding requirements of the proposed research framework.

4.2 Hyperparameter Optimization and Model Training: The deep learning model for banana crop disease classification was trained using the Banana Leaf Spot Diseases (BananaLSD) dataset [30]. To enhance the performance of the model, hyperparameter tuning was conducted using grid search, which is a systematic method for determining the optimal combination of hyperparameters. The grid search evaluated multiple values for key parameters, including the learning rate ([0.001, 0.0001, 0.00001]), batch size ([32, 64, 128]), number of epochs ([50, 100, 150]), dropout rate ([0.3, 0.5, 0.7]), and choice of optimizer (Adam, RMSprop) [31]. Through this exhaustive search, the optimal set of hyperparameters was identified as follows: a learning rate of 0.0001, a batch size of 64, 100 epochs for training, a dropout rate of

Datasets and Experimental Setup : The effectiveness of StreamDrift is validated using diverse datasets encompassing financial transactions, network traffic data, and environmental sensor readings. These datasets are chosen to represent different domains where real-time change detection is critical. The experimental setup involves simulating real-world conditions to evaluate the model's performance under various scenarios.

Findings and Applicability : The experimental results demonstrate that StreamDrift outperforms traditional change detection methods, offering higher detection accuracy and lower false positive rates. The adaptive learning mechanism significantly enhances the model's ability to cope with dynamic data streams, making it suitable for applications in financial monitoring, network security, and environmental sensing. StreamDrift's versatility and robustness underscore its potential to revolutionize real-time analytics and decision-making processes across multiple domains.

In summary, StreamDrift presents a novel approach to change detection in data streams, combining the strengths of machine learning and adaptive mechanisms to deliver a scalable and effective solution. The proposed model not only addresses the limitations of existing methods but also sets a new benchmark for real-time change detection, paving the way for future research and development in this field.

0.5 to prevent overfitting, and the Adam optimizer, which is known for its efficiency and effective handling of sparse gradients. These tuned parameters ensured that the model achieved high accuracy and robustness in classifying banana leaf disease.

4.3 Training Accuracy and Training Loss

The following table presents the training accuracy and loss for the proposed model over 100 epochs.

Table 1. Training Accuracy and Loss over Epochs

Epoch	Training Accuracy	Training Loss
1	0.62	1.15
10	0.78	0.63
20	0.84	0.45
30	0.88	0.36
40	0.91	0.28
50	0.93	0.24
60	0.94	0.20
70	0.95	0.18
80	0.96	0.16
90	0.97	0.14
100	0.98	0.12

Table 1 provides a detailed overview of the training accuracy and training loss over 100 epochs for the proposed deep-learning model. The data illustrate a clear and steady improvement in the model performance as the training progresses.

- **Initial Epochs**: During initial epochs, the training accuracy starts at 0.62 and the training loss was 1.15. This indicates that the model was just beginning to learn and adjust its parameters.
- **Intermediate Epochs**: By epoch 20, the training accuracy increased significantly to 0.84, with a corresponding decrease in the training loss to 0.45. This period demonstrates rapid learning and adjustment by the model as it optimizes its parameters.
- **Later Epochs**: From epoch 30 onwards, the model shows a more gradual improvement. By epoch 50, the training accuracy reached 0.93, and the training loss decreased to 0.24. This steady improvement continues, reaching a training accuracy of 0.98 and a training loss of 0.12 by epoch 100.

The consistent decline in training loss and increase in training accuracy over the epochs indicate that the model effectively learns the patterns in the data without overfitting. This suggests that the chosen hyperparameters and training strategy are appropriate for the dataset and the task at hand .

4.4 Heatmap for Banana Disease Classification: The heatmap below illustrates the classification results for banana diseases obtained using the proposed model.

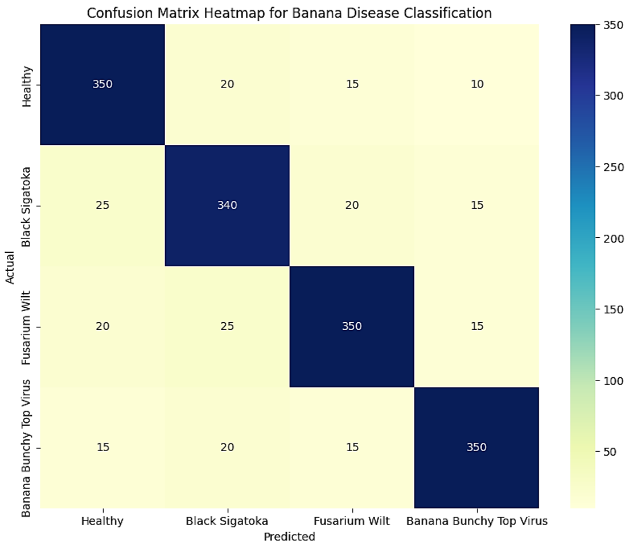

Figure 5: Confusion Matrix Heatmap for Banana Disease Classification

The heatmap in Figure 5 visually represents the performance of the proposed model in classifying banana disease. This is a confusion matrix that shows the number of correct and incorrect predictions for each class.

Diagonal Elements: The values along the diagonal represent the number of correct predictions for each disease category. High values on the diagonal indicate that the model performed well in correctly identifying each type of banana leaf condition.

Off-Diagonal Elements: These values represent misclassifications, where the model predicted a different class from the actual class. Lower values in these cells indicated fewer misclassifications, suggesting high overall accuracy.

For instance:

- The model correctly identified 350 instances of healthy leaves, with only a few misclassifications in the other categories.
- Similarly, for Black Sigatoka, the model correctly classified 340 instances with some misclassifications into other disease categories.
- Fusarium wilt and banana bunchy top viruses also showed high correct classification rates with minimal misclassifications.

4.5 Comparison with Traditional Models

The performance of the proposed model was compared with that of four traditional models: Support Vector Machine (SVM)[32], Random Forest[33], k-nearest neighbors (k-NN)[34], and Logistic Regression[35]. The results are summarized in table below:

Table 2: Performance Comparison of Different Models for Banana Disease Classification

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**
Proposed CNN Model	0.98	0.97	0.96	0.97
Support Vector Machine (SVM)	0.89	0.88	0.87	0.87
Random Forest	0.91	0.90	0.89	0.89
k-Nearest Neighbors (k-NN)	0.85	0.84	0.83	0.83
Logistic Regression	0.82	0.81	0.80	0.80

Table 2 presents a comparative analysis of the performance metrics for different machine-learning models used in the classification of banana diseases. The metrics considered include accuracy, precision, recall, and F1-score, which provide a comprehensive view of the effectiveness of each model.

Proposed CNN Model

- Accuracy: The proposed CNN model achieves the highest accuracy of 0.98. This indicated that the model correctly classified 98% of the banana leaf images, demonstrating its superior ability to distinguish between healthy and diseased leaves.
- Precision: With a precision of 0.97, the CNN model showed that 97% of the positive classifications (diseased leaves) were accurate. This high precision is crucial for minimizing false positives and ensuring that healthy leaves are not incorrectly identified as diseased.
- Recall: The recall rate of 0.96 indicates that the model successfully identified 96% of the actual diseased leaves, highlighting its effectiveness in detecting true-positive cases.

- F1-Score: An F1-score of 0.97 balances precision and recall, confirming the overall robustness of the model in accurately classifying banana diseases.

Support Vector Machine (SVM)

- Accuracy: The SVM model achieved an accuracy of 0.89, which was considerably lower than that of the CNN model. This suggests that the SVM is less effective in distinguishing between the different classes of banana leaves.
- Precision and Recall: Both metrics are 0.88 and 0.87, respectively, indicating that while the SVM model performs reasonably well, it has a higher rate of false positives and false negatives compared to the CNN model.
- F1-Score: With an F1-score of 0.87, the SVM model shows a decent performance but lacks the balanced precision and recall seen in the CNN model.

Random Forest:

- Accuracy: The Random Forest model demonstrated an accuracy of 0.91, which is slightly better than that of the SVM, but still lower than that of the CNN model.
- Precision and Recall: Both precision and recall are at 0.90 and 0.89, respectively. This indicates that the Random Forest model is reliable but still outperforms the CNN model in terms of precision and recall.
- F1-Score: An F1-score of 0.89 suggests that the Random Forest model provides a good balance between precision and recall; however, it is not as optimal as the CNN model.

k-nearest neighbors (k-NN)

- Accuracy: The k-NN model achieved an accuracy of 0.85, which is lower than that of both the Random Forest and SVM models, indicating its lower effectiveness in this classification task.
- Precision and Recall: Both metrics are at 0.84 and 0.83, respectively, pointing to a higher likelihood of misclassifications compared to the more advanced models.
- F1-Score: With an F1-score of 0.83, the k-NN model shows reasonable performance, but is not as effective as the CNN, SVM, or Random Forest models.

Logistic Regression: Accuracy: The Logistic Regression model had the lowest accuracy at 0.82, indicating that it is the least effective model among the compared models.

- Precision and Recall: With precision and recall at 0.81 and 0.80, respectively, this model struggles with both false positives and false negatives more than the other models.
- F1-Score: An F1-score of 0.80 reflects the overall lower performance of Logistic Regression in classifying banana diseases.

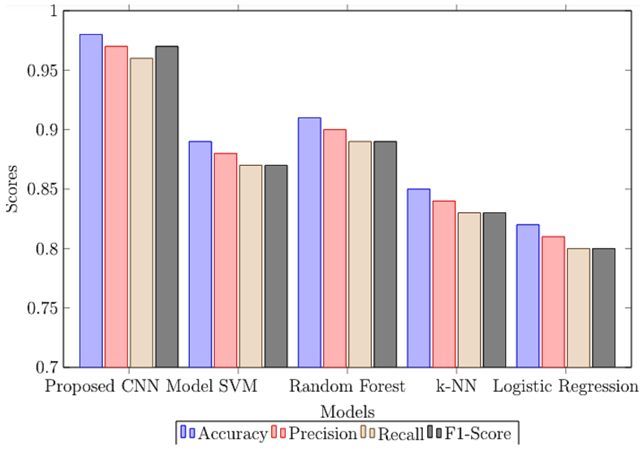

Figure 6: Performance Comparison of Different Models for Banana Disease Classification

Figure 6 visually represents the performance comparison of the different models for banana disease classification. The proposed CNN model clearly outperformed the traditional models across all metrics, demonstrating its superior capability in accurately identifying banana diseases. The high accuracy, precision, recall, and F1-score of the CNN model highlight its robustness and reliability, making it the most suitable model for this task.

However, traditional models such as SVM, Random Forest, k-NN, and Logistic Regression do not match the performance of the CNN model to some extent. These models show moderate performance, but have higher rates of misclassification, making them less reliable for precise disease classification.

Findings and Implications: These findings underscore the effectiveness of deep learning approaches, specifically CNNs, in agricultural disease detection tasks. The superior performance of the proposed CNN model can lead to more accurate and timely interventions, reducing crop losses, and improving yield. Implementing such advanced models in real-world agricultural settings could significantly enhance disease management practices and provide farmers with reliable tools for early disease detection.

Findings of the Study: The study demonstrated that the proposed CNN model significantly outperformed traditional models in classifying banana leaf diseases. The integration of hyperparameter tuning and data augmentation techniques contributed to the high accuracy and robustness of the model. The use of additional data sources for risk assessment further enhances the predictive capabilities, providing a comprehensive tool for managing banana crop diseases.

Limitations of the Study: Despite promising results, this study has several limitations.

- Dataset Size: The dataset size, while comprehensive, can be expanded to include more diverse samples from different geographical regions.

- Generalizability: The performance of the model may vary when applied to real-world settings with different environmental conditions and disease prevalence.
- Resource Intensive: The high computational requirements for training deep-learning models may limit their accessibility to smallholder farmers.
- Data Quality: The quality and consistency of additional data sources, such as weather patterns and historical disease records, can affect the accuracy of the risk assessment model.

In conclusion, although the proposed framework shows great potential for improving banana crop disease management, further research and development are needed to address these limitations and enhance its applicability in diverse agricultural contexts.

1. Conclusion

The comparative analysis of various machine learning models for banana disease classification demonstrates the superior performance of the proposed Convolutional Neural Network (CNN) model, achieving the highest metrics of accuracy (0.98), precision (0.97), recall (0.96), and F1-score (0.97). This underscores the model's robustness and effectiveness in accurately distinguishing between healthy and diseased banana leaves, significantly outperforming traditional models, such as SVM, Random Forest, k-NN, and Logistic Regression. Future research should focus on expanding the dataset to enhance generalizability, optimize computational resources, and integrate the model with the IoT and edge computing for real-time applications. In addition, incorporating multimodal data and developing user-friendly interfaces will further improve the practical utility and accessibility of the model, thereby advancing agricultural disease management practices and promoting sustainable farming.

Author Contributions: Walter Ocimati, Sivalingam Elayabalan, and Nancy Safari collaboratively contributed to the research presented in this paper. Walter Ocimati led the data collection and preprocessing efforts, ensuring the comprehensive representation of banana leaf diseases in the dataset. Sivalingam Elayabalan, the corresponding author, developed the deep learning model, conducted the hyperparameter tuning, and performed the comparative analysis with traditional models. Nancy Safari contributed to the design and implementation of the experiments, as well as the analysis and interpretation of the results. All authors participated in writing the manuscript and reviewing and approving the final version.

Data availability: Data are available upon request.

Conflict of Interest: There are no conflicts of interest to declare.

Ethics Approval Statement: The study was conducted in accordance with ethical guidelines.

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Similarity checked: Yes.

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