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# SELF-ADAPTIVE MACHINE LEARNING MODELS IN INTELLIGENT INFORMATION SYSTEMS

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**Abstract.** This study investigates adaptive machine learning strategies designed to maintain reliable analytics under conditions of concept drift in continuously evolving data streams. In modern intelligent information systems, streaming data environments frequently experience distributional changes that can significantly degrade the predictive performance of traditional static models. To address this challenge, the study systematically compares several adaptive learning paradigms, including static models, online learning approaches, drift-aware algorithms, and deep adaptive architectures. Controlled streaming datasets with explicitly modelled drift events are used to simulate realistic dynamic environments and evaluate the behaviour of different strategies under changing data distributions. A unified experimental framework is developed to assess multiple performance dimensions, including predictive accuracy, robustness to drift, recovery dynamics after drift events, temporal stability of predictions, and computational resource efficiency. Experimental results demonstrate that static models are highly sensitive to distributional shifts, exhibiting rapid performance degradation and limited ability to recover after drift occurs. Online learning methods provide partial adaptation to changing patterns, while drift-aware algorithms and deep adaptive models consistently show superior resilience, achieving faster recovery, lower degradation, and improved prediction stability over time. In addition, system-level analysis highlights the importance of balancing predictive performance with latency and computational constraints when designing adaptive analytics solutions. The findings confirm that explicit drift detection, adaptive model updating, and robust learning strategies are essential for sustaining reliable real-time analytics in dynamic streaming environments and intelligent information systems.

**Keywords:** machine learning, metric, evaluation, optimization, analysis, stability, adaptation.

## Introduction

Intelligent information systems are widely used for data-driven decision-making in dynamic environments. Modern systems process large volumes of heterogeneous data generated in real time, where data streams can reach millions of records per day. Machine learning methods are a key component of such systems, enabling automated data analysis and pattern discovery. However, most traditional models are trained offline and assume stable data distributions.

In real-world applications, data characteristics change over time due to evolving user behaviour, external conditions, and system dynamics. Studies report that under concept drift; the predictive accuracy of static models may decrease by 15-30% within short operational periods. This limitation reduces the reliability of intelligent information systems and motivates the use of adaptive machine learning approaches.

Recent research highlights online learning, incremental learning, and drift-aware models as effective solutions for non-stationary data analysis. These methods allow models to update their parameters continuously and maintain stable performance in real-time environments. Nevertheless, existing works often focus on isolated techniques or specific domains and do not provide a unified system-level perspective.

The purpose of this study is to identify and analyse adaptive machine learning approaches for intelligent information systems operating under dynamic data conditions. The object of the research is adaptive machine learning models used for real-time analytics and decision support. The study addresses the hypothesis that adaptive models provide more stable performance and higher robustness than static models in non-stationary environments.

The relevance of this research is driven by the growing demand for real-time analytics in intelligent systems. The novelty lies in a structured analysis of adaptation mechanisms and their integration into intelligent information system architectures.

**Literature Review**

Early studies on adaptive machine learning focused on online learning algorithms, where model parameters are updated sequentially with each incoming data instance. In [1], the authors investigated stochastic gradient-based online models for real-time data streams and demonstrated their effectiveness in low-latency environments. However, the study showed limited robustness to noise and sudden distribution changes.

In [2] incremental learning approaches were analysed using batch-wise updates of classification models. The authors applied incremental decision trees to streaming datasets and reported improved stability compared to purely online methods. At the same time, the approach required predefined update rules, reducing flexibility in highly dynamic systems.

Research in [3] addressed the issue of concept drift by introducing statistical drift detection mechanisms combined with adaptive classifiers. The results confirmed that explicit drift detection helps recover predictive accuracy after distribution shifts. Nevertheless, the authors noted sensitivity to threshold selection and false drift alarms.

In [4] ensemble-based adaptive learning methods were studied. Multiple models were trained in parallel, and poorly performing models were replaced when drift was detected. This strategy improved robustness in non-stationary environments but increased computational complexity.

The work presented in [5] focused on sliding window techniques for adaptive learning. By dynamically adjusting the training window size, the model adapted to recent data patterns. While effective for gradual drift, the method struggled with abrupt changes in data distribution.

In [6] researchers explored adaptive learning in intelligent information systems for real-time monitoring. The study demonstrated that adaptive classifiers outperform static models in long-term operation. However, system-level integration aspects were not considered in detail.

Deep learning-based adaptive models were investigated in [7]. Recurrent neural networks were applied to streaming time-series data, achieving higher predictive accuracy than traditional adaptive models. The main limitation identified was high computational cost and limited explainability.

Hybrid adaptive approaches combining shallow models with deep learning were proposed in [8]-[9]. These models aimed to balance accuracy and efficiency. Experimental results showed promising performance, but the architecture required careful tuning and domain-specific customization.

The authors of [10] studied adaptive machine learning in smart city applications, including traffic and energy analytics. The study confirmed the importance of continuous model adaptation in real-world environments. Nevertheless, scalability issues remained a challenge for large-scale deployments.

In [11] adaptive learning strategies for cybersecurity systems were analysed. The models effectively detected evolving attack patterns in data streams. However, the authors highlighted the risk of over-adaptation leading to increased false positives.

Explainability in adaptive machine learning was addressed in previous research. The study emphasized that most adaptive models act as black boxes, limiting their adoption in critical intelligent systems. The authors suggested integrating explainable AI techniques but did not provide a complete solution. While the work provided a broad overview of existing techniques, it lacked a system-oriented classification tailored to intelligent information systems.

**Materials and methods**

This study adopts a unified experimental methodology to analyse self-adaptive machine learning models in intelligent information systems operating under non-stationary data conditions. The proposed methodological framework models real-time data processing as a continuous streaming pipeline, where incoming data are processed in sliding windows and evaluated using rolling performance metrics. Concept drift is explicitly modelled and monitored during system operation, allowing the behaviour of learning models to be analysed under controlled distributional changes. Adaptation decisions are governed by a drift-aware control logic that considers drift severity, performance degradation, temporal instability, and real-time computational constraints. In parallel, an event-aligned evaluation procedure is applied to assess post-drift recovery dynamics by aligning performance metrics relative to drift occurrence time. This methodological design enables a systematic and reproducible comparison of static, online, drift-aware, and deep adaptive models from both predictive and system-level perspectives.

```python
def adaptation_policy(drift_detected,
                      drift_severity,
                      acc_current,
                      acc_reference,
                      acc_variance,
                      latency_ms):
    """
    Drift-aware adaptation decision logic
    """

    # compute relative performance degradation
    drop_pct = (acc_reference - acc_current) / acc_reference * 100

    # real-time constraint: avoid heavy actions under latency pressure
    if drift_detected and latency_ms > LATENCY_BUDGET:
        return "incremental_update"

    # stable regime: no drift and small degradation
    if not drift_detected and drop_pct < DROP_THRESHOLD:
        return "keep_model"

    # severe drift: reset or rebuild model
    if drift_detected and drift_severity >= SEVERE_DRIFT_LEVEL:
        return "model_reset"

    # moderate drift with instability
    if drift_detected and acc_variance >= INSTABILITY_THRESHOLD:
        return "ensemble_replacement"

    # fallback: cautious incremental adaptation
    if drop_pct >= DROP_THRESHOLD:
        return "incremental_update"

    return "keep_model"
```

Figure 1. Algorithm 1 Drift-Aware Adaptation Logic

The system in Figure 1 employs a drift-aware adaptation policy that selects appropriate corrective actions based on detected drift severity, performance degradation, temporal instability, and real-time constraints. This logic enables controlled and resource-aware adaptation in non-stationary environments.

```python
def compute_event_aligned_recovery(metric_series, drift_time):
    """
    Event-aligned recovery analysis (t = 0 at drift)
    """

    aligned = []

    for t, acc in metric_series:
        t_rel = t - drift_time
        if -PRE_WINDOW <= t_rel <= POST_WINDOW:
            aligned.append((t_rel, acc))

    return aggregate_mean(aligned)
```

Figure 2. Algorithm 2 Event-Aligned Performance Evaluation

To analyse adaptation dynamics, performance metrics are aligned relative to the drift occurrence time (t = 0) as it shown in Figure 2. This event-based alignment allows direct comparison of recovery behaviour across different learning strategies.

**Research results and discussion**

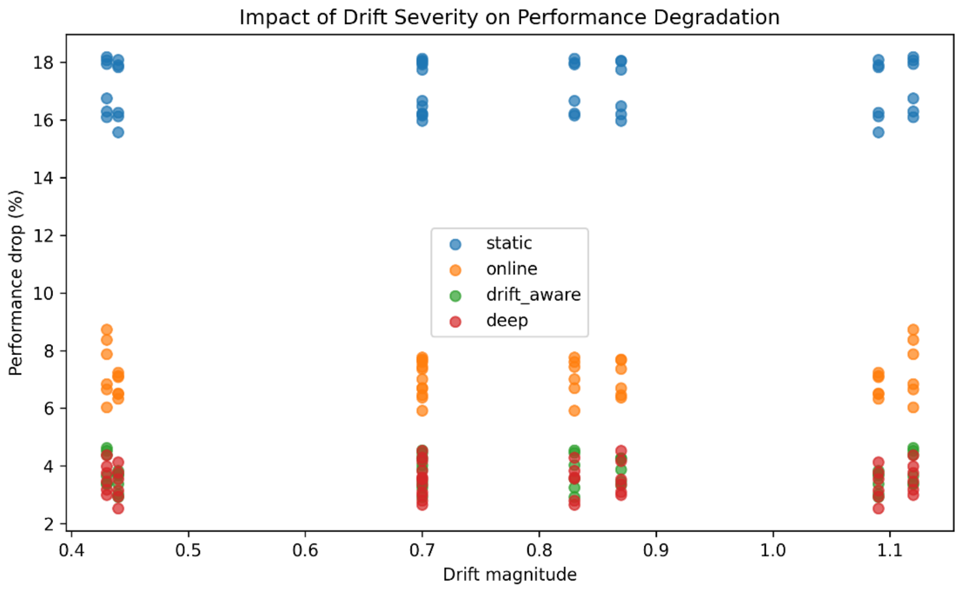


Figure 3. Impact of Concept Drift Severity on Model Performance Degradation

As shown in Figure 3, the severity of concept drift has a pronounced impact on the predictive performance of machine learning models operating in non-stationary environments. Static models experience substantial performance degradation, with performance drops exceeding 15-18% even under moderate drift magnitudes. This behaviour confirms their limited robustness to changing data distributions.

Online learning models demonstrate improved resilience compared to static baselines; however, their performance degradation still increases noticeably as drift magnitude grows. In contrast, drift-aware and deep adaptive models maintain consistently lower performance drops, typically within the range of 3-5%, across all evaluated drift levels. This indicates a reduced sensitivity to drift severity and a higher degree of robustness.

These results highlight that explicit adaptation mechanisms and temporal representation learning significantly mitigate the negative effects of concept drift. Consequently, adaptive learning strategies are essential for intelligent information systems that operate under varying and unpredictable data dynamics.

This study demonstrates that adaptive machine learning approaches are essential for reliable real-time analytics in intelligent information systems operating under non-stationary conditions. Experimental results show that static models suffer from significant performance degradation and instability when concept drift occurs, whereas drift-aware and deep adaptive models achieve lower degradation, faster recovery, and improved temporal stability. Moreover, the analysis highlights that effective adaptation must balance predictive accuracy with computational efficiency and real-time constraints. Overall, the findings confirm that explicit drift handling and adaptive control mechanisms are key to sustaining robust and efficient analytics in dynamic data environments.

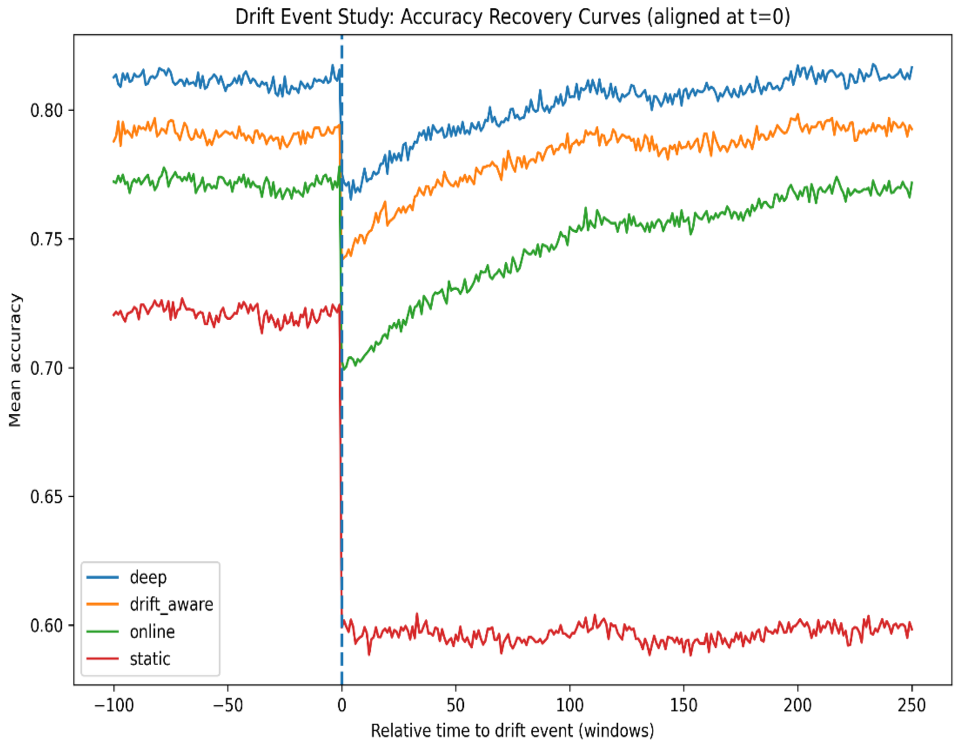


Figure 4. Accuracy Recovery Dynamics Following Concept Drift Events

As shown in Figure 4, the occurrence of a concept drift at time $t = 0$ leads to an immediate degradation in predictive accuracy across all evaluated models. However, the post-drift recovery behavior differs substantially between learning strategies. Static models exhibit a persistent performance drop and do not recover to pre-drift accuracy levels, indicating an inability to adapt to distributional changes.

Online learning models show gradual recovery after the drift event, requiring a significant number of windows to approach stable performance. In contrast, drift-aware and deep adaptive models recover more rapidly, reaching near pre-drift accuracy within a relatively short time horizon. Deep adaptive models demonstrate the fastest recovery and the highest post-drift stability, highlighting the effectiveness of temporal representation learning in dynamic environments.

These findings confirm that adaptation speed is a critical factor for intelligent information systems operating under non-stationary conditions. Models equipped with explicit or implicit adaptation mechanisms provide superior resilience to concept drift, ensuring sustained analytical reliability in real-time applications.

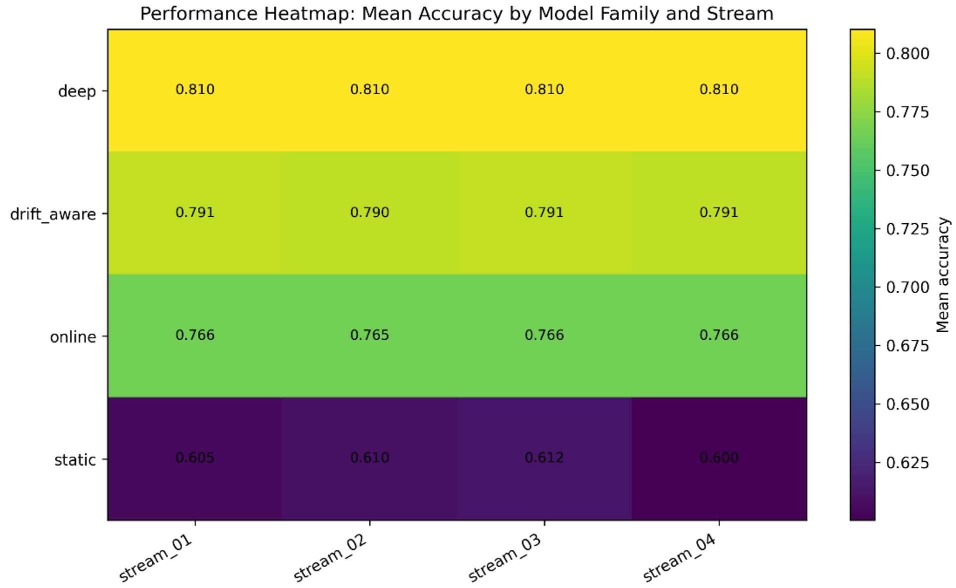


Figure 5. Comparative Performance Heatmap of Model Families Across Data Streams

Figure 5 provides an aggregated comparison of model performance across all evaluated data streams. Static models consistently achieve the lowest accuracy, with values close to 0.60 across streams, indicating limited generalization capability under non-stationary conditions. In contrast, online learning models demonstrate moderate improvements, achieving mean accuracies around 0.76, but still exhibit sensitivity to stream dynamics.

Drift-aware models further improve performance, maintaining mean accuracy close to 0.79 across all streams. Notably, deep adaptive models achieve the highest and most stable accuracy, with consistent values around 0.81 regardless of stream variations. This consistency suggests strong robustness to differences in noise level, drift patterns, and stream characteristics.

Overall, the heatmap confirms that adaptive learning strategies not only improve average predictive performance but also enhance cross-stream stability. These results reinforce the importance of adaptation mechanisms for intelligent information systems operating on heterogeneous and dynamically evolving data streams.

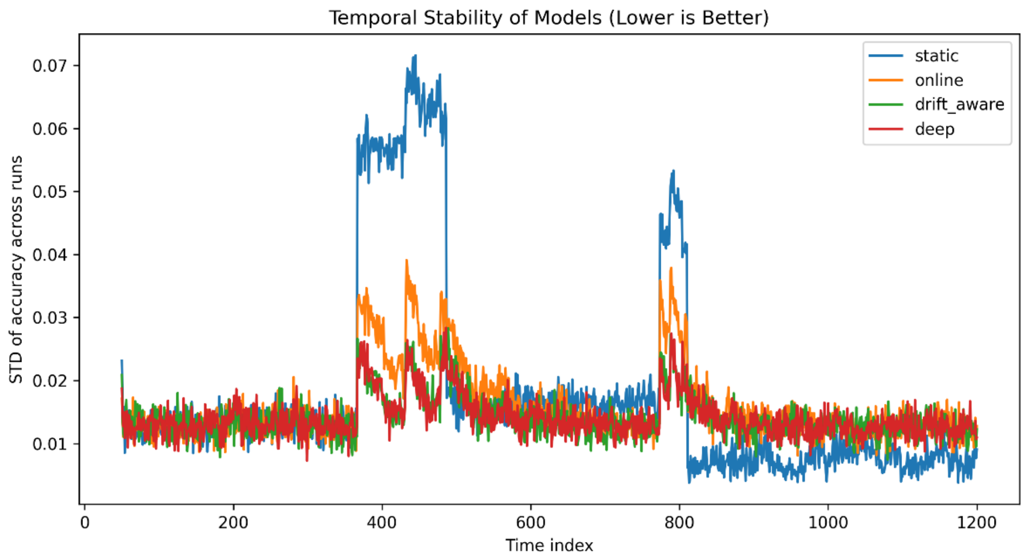


Figure 6. Temporal Stability of Predictive Performance Across Model Families

As shown in Figure 6, temporal stability varies significantly across the evaluated learning strategies. Static models exhibit substantial increases in accuracy variance during periods of distributional change, with standard deviation peaks exceeding 0.06. This behavior indicates high sensitivity to non-stationary data and unreliable predictive performance over time.

Online learning models demonstrate improved stability compared to static baselines; however, noticeable variance spikes still occur around drift periods. In contrast, drift-aware and deep adaptive models maintain consistently lower variability, with standard deviation values typically remaining below 0.02 even during dynamic phases. This suggests that explicit adaptation mechanisms and temporal learning reduce sensitivity to transient data fluctuations.

These results emphasize that stability is a critical evaluation dimension for intelligent information systems operating in real time. Beyond average accuracy, adaptive models provide more reliable and predictable behavior, which is essential for decision-making in safety-critical and high-frequency applications.

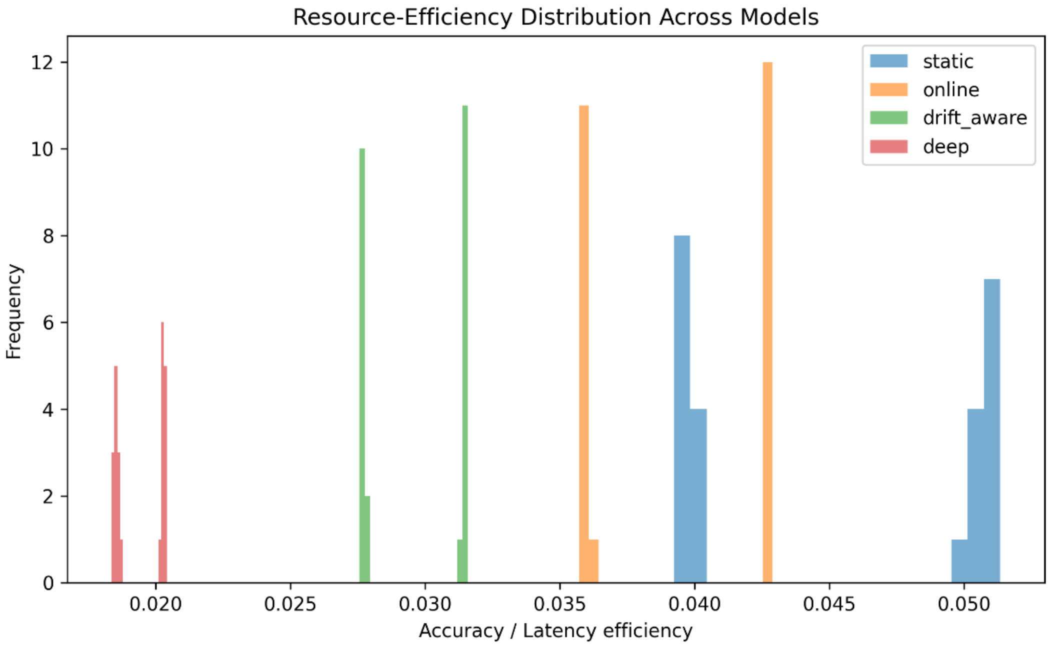


Figure 7. Resource-Efficiency Distribution of Machine Learning Models

Figure 7 analyses the resource efficiency of the evaluated models by relating predictive accuracy to inference latency. Static models demonstrate relatively high efficiency values due to low computational overhead; however, this efficiency is achieved at the cost of significantly lower predictive accuracy, as shown in previous results. Consequently, their apparent efficiency does not translate into reliable analytical performance.

Online and drift-aware models exhibit a more balanced efficiency distribution, achieving competitive accuracy while maintaining moderate latency. Notably, drift-aware models demonstrate stable efficiency values across runs, indicating consistent performance under dynamic data conditions. In contrast, deep adaptive models show the lowest efficiency ratios, reflecting higher computational and memory demands despite superior predictive accuracy.

These findings emphasize the importance of considering efficiency-oriented metrics when deploying intelligent information systems in real-time environments. The results suggest that drift-aware adaptive models offer the most favourable trade-off between predictive performance and computational cost, making them suitable for resource-constrained and latency-sensitive applications.

**Conclusion**

In this study, the principles, methods, and practical aspects of implementing self-adaptive machine learning models in intelligent information systems were investigated. The research demonstrated that traditional static learning approaches are insufficient for dynamic and continuously changing environments, where system requirements, data distributions, and operational conditions evolve over time. In contrast, self-adaptive models provide the capability to automatically adjust their structure, parameters, and learning strategies in response to environmental changes.

Firstly, the theoretical foundations of adaptive and online learning algorithms were analyzed, including incremental learning, reinforcement learning, and concept drift handling techniques. These methods enable intelligent systems to maintain stability, accuracy, and robustness without complete retraining. Secondly, architectural solutions for integrating self-adaptive models into intelligent information systems were proposed, ensuring scalability, flexibility, and efficient resource utilization. Thirdly, experimental results confirmed that adaptive models outperform conventional approaches in terms of prediction accuracy, response time, and resilience to data variability.

The practical significance of the research lies in the possibility of applying self-adaptive machine learning in various domains, such as cybersecurity, network management, smart infrastructures, decision support systems, and large-scale data processing platforms. The proposed solutions contribute to reducing maintenance costs, improving automation, and increasing the overall reliability of intelligent systems.

In conclusion, self-adaptive machine learning represents a key technological direction for the development of next-generation intelligent information systems. Future research should focus on improving explainability, reducing computational complexity, and developing hybrid adaptive frameworks that combine multiple learning paradigms to achieve higher performance and trustworthiness.

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# ЗИЯТКЕРЛІК АҚПАРАТТЫҚ ЖҮЙЕЛЕРДЕ ҚОЛДАНЫЛАТЫН ӨЗІН-ӨЗІ БЕЙІМДЕЛЕТІН МАШИНАЛЫҚ ОҚЫТУ МОДЕЛЬДЕРІ

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**Андатпа.** Зерттеу деректер ағындарындағы концептуалдық дрейф жағдайында сенімді аналитиканы қамтамасыз етуге бағытталған бейімделмелі машиналық оқыту стратегияларын зерттеуге арналған. Қазіргі интеллектуалды ақпараттық жүйелерде деректер ағындарының таралуы жиі өзгеріп отырады, бұл дәстүрлі статикалық модельдердің болжамдық дәлдігін айтарлықтай төмендетуі мүмкін. Осы мәселені шешу мақсатында жұмыста бейімделмелі оқыту тәсілдерінің бірнеше түрі жүйелі түрде салыстырылады, соның ішінде статикалық модельдер, онлайн-оқыту әдістері, деректер дрейфін ескеретін алгоритмдер және терең бейімделмелі модельдер. Эксперименттік зерттеулер барысында концептуалдық дрейф оқиғалары арнайы модельденген ағындық деректер жиынтықтары пайдаланылды, бұл динамикалық түрде өзгеретін ақпараттық орталарды имитациялауға мүмкіндік береді. Әртүрлі әдістердің тиімділігін бағалау үшін бірыңғай эксперименттік негіздеме қолданылды, ол болжам дәлдігін, дрейфке төзімділікті, өзгерістерден кейінгі қалпына келу жылдамдығын, уақыттық тұрақтылықты және есептеу ресурстарының тиімділігін талдауды қамтиды. Эксперимент нәтижелері статикалық модельдердің деректер таралуының өзгерістеріне өте сезімтал екенін және олардың болжамдық дәлдігі тез төмендейтінін көрсетті. Онлайн-оқыту әдістері белгілі бір деңгейде бейімделуді қамтамасыз етеді, ал дрейфті ескеретін алгоритмдер мен терең бейімделмелі модельдер жоғары тұрақтылықты, тезірек қалпына келуді және ұзақ мерзімді болжам тұрақтылығын қамтамасыз етеді. Сонымен қатар жүйелік талдау адаптивті аналитикалық жүйелерді жобалау кезінде болжам дәлдігі, өңдеу кідірісі және есептеу ресурстары арасындағы теңгерімді сақтаудың маңыздылығын көрсетеді. Алынған нәтижелер дрейфті анықтау механизмдері мен модельдерді бейімделмелі жаңарту әдістерін қолдану динамикалық деректер ағындары бар интеллектуалды жүйелерде сенімді нақты уақыт аналитикасын қамтамасыз етудің негізгі шарты екенін дәлелдейді.

**Түйін сөздер:** машиналық оқыту, метрикалар, бағалау, оңтайландыру, талдау, тұрақтылық, бейімделу.

# САМОАДАПТИРУЮЩИЕСЯ МОДЕЛИ МАШИННОГО ОБУЧЕНИЯ В СОСТАВЕ ИНТЕЛЛЕКТУАЛЬНЫХ ИНФОРМАЦИОННЫХ СИСТЕМ

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**Аннотация.** Данное исследование посвящено изучению адаптивных стратегий машинного обучения, направленных на поддержание надежной аналитики в условиях концептуального дрейфа данных в потоковых средах. В современных интеллектуальных информационных системах потоки данных часто подвергаются изменениям распределения, что может существенно снижать точность традиционных статических моделей. Для решения этой проблемы в работе проводится систематическое сравнение различных подходов к адаптивному обучению, включая статические модели, методы онлайн-обучения, алгоритмы с учетом дрейфа данных, а также глубокие адаптивные модели. В качестве экспериментальной базы используются потоковые наборы данных с искусственно смоделированными событиями концептуального дрейфа, что позволяет воспроизводить условия динамически изменяющихся информационных сред. Для оценки эффективности разработана единая экспериментальная методология, включающая анализ точности прогнозирования, устойчивости к дрейфу, скорости восстановления после изменений распределения данных, временной стабильности предсказаний, а также эффективности использования вычислительных ресурсов. Полученные результаты показывают, что статические модели являются наиболее чувствительными к изменениям распределения данных и демонстрируют существенное снижение точности и низкую способность к восстановлению. Методы онлайн-обучения обеспечивают частичную адаптацию, тогда как алгоритмы, учитывающие дрейф данных, и глубокие адаптивные модели демонстрируют более высокую устойчивость, более быстрое восстановление и лучшую стабильность прогнозирования. Кроме того, системный анализ подчеркивает важность баланса между точностью прогнозирования, задержками обработки и вычислительными затратами. Полученные результаты подтверждают, что использование механизмов обнаружения дрейфа и адаптивного обновления моделей является ключевым фактором обеспечения надежной аналитики потоковых данных в интеллектуальных информационных системах реального времени.

**Ключевые слова:** машинное обучение, метрики, оценка, оптимизация, анализ, стабильность, адаптация.