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Topic	Content Based Recommendation System Using Computational Intelligence and Machine Learning
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Finding	**1.** A Novel Approach to Movie Recommendation Systems: Overcoming the Cold Start Problem with Dynamic Sea-Horse Slimmable Network with a Contextual Attention Network. **2.** An Enhanced Sentiment Analysis Based Recommendation System Integrating with Content Based Filtering and Multi-Instance Depthwise Seperable Network. **3.** Dual Discriminator Generative Adversarial Diffusion Kernel Attention Network based Content and Collaborative filtering in Recommendation System Modelling and Simulation. **4.** Advancing Time-Based Recommendations in Collaborative Filtering: Evaluating Performance with Parallel Walrus Hyperbolic Convolutional Attention Graph Networks.
Abstract	In the rapidly evolving digital landscape, recommendation systems (RS) play a critical role in enhancing user engagement by offering personalized content across domains such as entertainment, e-commerce, and online services. However, conventional RS techniques are challenged by issues such as data sparsity, the cold start problem, poor interpretability of unstructured data like reviews, and inadequate modeling of complex user-item interactions. To overcome these limitations, this thesis introduces four novel deep learning-based frameworks that aim to improve accuracy, personalization, and efficiency of recommendation systems by integrating advanced neural architectures, optimization algorithms, and hybrid filtering strategies. This thesis introduces four novel frameworks designed to enhance recommendation systems, with each chapter focusing on a distinct architecture and domain-specific challenge. The first chapter presents a Dynamic Sea-Horse Slimmable Network with Contextual Attention Network (DSHS-ConAtNet), aimed at addressing data sparsity and cold start issues in movie recommendation systems. The framework is evaluated using four MovieLens datasets (Original 100K, Original 1M, Resampled 100K, and Resampled 1M). Preprocessing is performed using Anisotropic Gaussian Filtering with a Directionally Truncated First Derivative to minimize noise, followed by high-order feature extraction using Scale-Aware Modulation and Transformer-Based architectures. The proposed model integrates DSHS-ConAtNet with Sea-Horse Optimizer for dynamic personalization and improved collaborative user-based filtering. Experimental analysis reveals that the model achieves an accuracy of 99% and a reduced RMSE of 0.6836, demonstrating its effectiveness in handling cold start conditions. The advantages of this model include high accuracy and efficient dynamic modelling, while its limitations involve higher computational complexity due to transformer usage. The second chapter focuses on improving recommendation accuracy in e-commerce by analysing user reviews through sentiment analysis. The proposed method, titled Multi-Instance Depthwise Separable Convolutional Neural Networks with Gooseneck Barnacle Optimization (MIDSCNN-GBO), combines sentiment analysis with content-based filtering. Feature extraction is accomplished using Absolute Deviation Factors-Class Document Frequency (ADF-CDF), and sentiment classification is handled by MIDSCNN, optimized through GBO. The approach is validated through various metrics, achieving an impressive 99% accuracy, and outperforming traditional systems in precision, F1-score, RMSE, MAPE, and MAE. This chapter demonstrates that unstructured textual reviews can be efficiently leveraged for personalized recommendations. Key advantages of this method include enhanced customization and robustness in review interpretation; however, challenges remain in handling ambiguous or sarcastic sentiment data. In the third chapter, a hybrid recommendation framework is introduced using Dual Discriminator Generative Adversarial Networks with Diffusion Kernel Attention and Green Anaconda Optimization (DDGANN-DKAN-GAO). This model addresses the need for combining collaborative and content-based filtering by processing data from the MovieLens 20M and 100K datasets. Preprocessing involves text cleaning, translation, blob calculation,

	and normalization. Feature extraction is conducted using ADF-CTF, while classification of user sentiment is performed by DDGANN-DKAN, with optimization driven by Green Anaconda Optimization. This hybrid strategy significantly boosts performance, achieving 99.92% accuracy, 99.93% precision, 98.78% recall, and 98.34% MAP. The advantages of this model lie in its dual filtering capability and GAN-based discrimination, though it is computationally intensive and sensitive to training stability due to the GAN structure. The fourth chapter proposes PWaHy-CAGNet, a Parallel Walrus Hyperbolic Convolutional Attention Graph Network, to capture complex user-item interactions and time-aware preferences. This model incorporates Grid-Constrained Data Cleansing for preprocessing and employs a combination of similarity metrics including Cosine, Pearson, and Gower's Coefficients. Additionally, it uses Exponential and Power Decay functions for refining temporal similarities. Hyperbolic convolution and attention mechanisms enhance the representational power of the model in non-Euclidean space. Evaluated on the MovieLens-100K dataset, PWaHy-CAGNet reaches 99% accuracy with a reduced RMSE of 0.6836 when combined with Gower's Coefficient and exponential decay. The model is advantageous due to its ability to capture intricate user behavior and integrate diverse similarity signals, though it may face scalability challenges on larger graphs and requires careful tuning of decay parameters. Together, these four frameworks contribute to the advancement of personalized recommendation systems by leveraging deep learning, attention mechanisms, optimization algorithms, and hybrid data representations