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RESEARCH ON GRID DATA ANALYSIS AND INTELLIGENT RECOMMENDATION SYSTEM BY INTRODUCING NEURAL TENSOR NETWORK MODEL

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Abstract. In the landscape of modern smart homes, the prevalence of intelligent devices, notably smart televisions (TVs), has surged, emphasizing the need for sophisticated content recommendation systems. However, the automatic provision of personalized content recommendations for smart TV users remains an underexplored domain. Existing literature has delved into recommendation systems across diverse applications, yet a distinctive void exists in addressing the intricate challenges specific to smart TV users, particularly the incorporation of the smart TV camera module for user image capture and validation. This research introduces a pioneering Intelligent Recommendation System for smart TV users, incorporating a novel Convolutional Neural Tensor Network (CNTN) model. The implementation of this innovative approach involves training the CNN algorithm on two distinct datasets "CelebFaces Attribute Dataset" and "Labeled Faces in the Wild-People" for proficient feature extraction and precise human face detection. The trained CNTN model processes user images captured through the smart TV camera module, matching them against a 'synthetic dataset.' Exploiting this matching process, a hybrid filtering technique is proposed and applied, seamlessly facilitating the personalized recommendation of programs. The proposed CNTN algorithm demonstrates an impressive training performance, achieving approximately 97.18%. Moreover, the hybrid filtering technique produces commendable results, attaining an approximate recommendation accuracy of 89% for single-user scenarios and 86% for multi-user scenarios. These findings underscore the superior efficacy of the hybrid filtering approach compared to conventional content-based and collaborative filtering techniques. The integration of the CNTN architecture and the hybrid filtering methodology collectively contributes to the development of an advanced and effective recommendation system tailored to the nuanced preferences of smart TV users in the context of grid data analysis.

Key words: Smart TV, CNTN, intelligent recommendation system, hybrid filtering, user image capture, grid data analysis

1. Introduction.

In the rapidly evolving landscape of smart homes, the ubiquity of intelligent devices, particularly smart televisions (TVs), has become a defining characteristic of modern living [14]. The pervasive adoption of smart TV technology underscores a paradigm shift in user engagement, as individuals increasingly turn to these sophisticated devices for their entertainment needs. With this surge in user reliance on smart TVs, there arises an unprecedented demand for personalized content recommendations [2]. Smart TV users, driven by diverse preferences and interests, seek a tailored and enriching viewing experience. Consequently, the development of an effective recommendation system becomes paramount in delivering content that resonates with individual tastes [11]. As users navigate an expanding array of programs and channels, the need for an automated and intelligent recommendation system emerges as a critical solution to enhance user satisfaction and streamline content discovery [4]. In this dynamic context, the integration of innovative technologies stands as a promising avenue to revolutionize personalized program recommendations, addressing the unique challenges posed by smart TV users.

Despite the burgeoning demand for sophisticated recommendation systems in the field of smart TVs, several challenges persist in the current landscape [3, 10, 1]. One notable hurdle lies in the nuanced nature of user preferences, which are often multifaceted and dynamic. Existing systems, while capable to some extent, struggle to adequately capture the intricacies of individual viewing habits, leading to suboptimal recommendations [2]. Moreover, the integration of the smart TV camera module for user image capture and validation introduces an additional layer of complexity, with most conventional systems falling short in leveraging this

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innovative capability. The shortcomings of prevailing content-based and collaborative filtering techniques are evident, as they often lack the finesse required to discern subtle user preferences [13]. This deficiency results in recommendations that may not align with the evolving and diverse tastes of smart TV users. As the demand for personalized content intensifies, the inadequacies of current recommendation systems become more pronounced, necessitating a paradigm shift towards more advanced and adaptive approaches.

Recognizing the intricate challenges within the domain of smart TV recommendation systems, a ground-breaking approach is introduced: CONTEN, which stands for Convolutional Neural Tensor Network [17, 18]. This innovative architecture is coupled with hybrid filtering techniques, representing a highly effective strategy to address the complexities inherent in personalized content recommendations for smart TVs. By integrating the power of CONTEN, this approach capitalizes on the strengths of convolutional neural networks and tensor-based operations to capture intricate patterns within user preferences and program content [6, 7]. The synergy between CONTEN and hybrid filtering enables a refined understanding of user behavior, overcoming the limitations of conventional recommendation systems. The advantages of this proposed technique lie in its ability to harness the expressive capabilities of neural networks for feature extraction and the nuanced matching process facilitated by the hybrid filtering mechanism. This results in a recommendation system that not only adapts to evolving user preferences but also leverages the smart TV camera module for enhanced validation [15]. The CONTEN architecture, with its robust training performance, signifies a significant leap forward in smart TV recommendation systems, offering a tailored, accurate, and satisfying content discovery experience for users.

The main contributions of the paper as follows

1. Proposed the novel approach of CONTEN the intelligent recommendation system for the smart TV users.
2. This suggested method leverages Convolutional Neural Tensor Network (CNTN) and Hybrid filtering process to achieve effective results.
3. The rigorous experiment of the study conducted with two datasets namely “CelebFaces Attribute Dataset” and “Labeled Faces in the Wild-People”.
4. The evaluations are prove with the effective experiments.

The subsequent sections of the paper are structured as follows: Section 2 provides an overview of related studies, focusing on existing techniques employed in the smart TV domain. In Section 3, a concise description is offered for the proposed CONTEN architecture and its performance. Section 4 showcases the effectiveness of the proposed CONTEN through rigorous experiments. The concluding remarks are presented in Section 5.

2. Related Work.

2.1. Intelligent Recommendation Systems in various domains. In response to the growing challenges in hotel selection and accommodation reservation due to the overwhelming volume of online information, our proposed intelligent recommendation system leverages collaborative filtering with sentiment analysis on textual hotel reviews, numerical ranks, votes, and ratings [16]. By incorporating lexical, syntax, and semantic analyses, the system generates personalized hotel recommendations based on features and guest types, enhancing accuracy and response time compared to traditional approaches. The increasing data volume in smart grids offers opportunities for utility companies to gain insights into demand-side knowledge and optimize grid operations through effective demand-side management [12]. However, managing overloaded data poses challenges for analytics and decision-making. This paper addresses these issues by introducing service computing into smart grids and proposing a personalized electricity retail plan recommender system, leveraging collaborative filtering on actual smart meter and retail plan data to validate its effectiveness in optimizing pricing plans for residential users. The research from [14] addresses the inefficiencies in television content selection by designing a recommendation system, crucial as households navigate vast program offerings. Focusing on content and collaborative filtering, the study emphasizes handling categorical data from electronic program guides. Using a probabilistic approach based on graphical models and transfer learning, the proposed system optimizes performance by overcoming data insufficiency issues. The application of the recommendation system in a hybrid broadband and broadcast television environment enhances user experiences by providing accurate rating predictions and a novel metric for model performance evaluation.

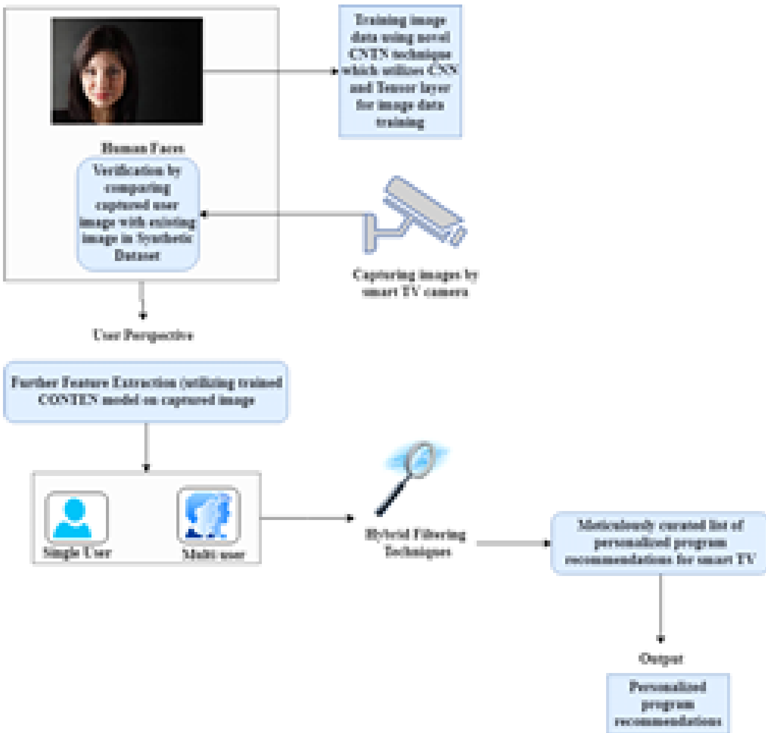

Fig. 3.1: Proposed CONTEN Architecture

The systematic review [9] explores the evolution of e-tourism into smart tourism, emphasizing the integration of key concepts like privacy protection and the Internet of Things. Analyzing 65 selected papers from 2013 to 2020, the study classifies smart tourism recommender systems into collaborative filtering, content model, context model, and hybrid model approaches, with the content model-based approach proving highly impactful. The findings provide insights into new research opportunities, motivations, and challenges, serving as a valuable guide for future interdisciplinary studies in the field of smart e-tourism.

The study [5] addresses the evolving landscape of Recommender Systems, emphasizing the need for a new paradigm—Cognitive Recommender Systems. Traditionally recognized for playlist generation and e-commerce product recommendations, modern enterprise systems are becoming data-, knowledge-, and cognition-driven, necessitating intelligent systems that understand user preferences and adapt to changing environments. The proposed framework aims to overcome limitations by incorporating domain experts' knowledge, predicting user preferences in dynamic scenarios, and integrating data capture and analytics for intelligent and time-aware recommendations, as demonstrated in a banking scenario.

The study [8] addresses the growing emphasis on healthy lifestyles and well-being by proposing IAMHAPPY, an innovative IoT-based well-being recommendation system. Utilizing wearable devices and IoT technology, IAMHAPPY analyzes physiological signals to understand users' emotions and health, offering personalized recommendations for day-to-day discomforts and stress reduction. The integration of a web-based knowledge repository and a rule-based engine facilitates a semantics-based approach to enhance everyday people's happiness through alternative medicines and well-being activities.

3. Methodology.

3.1. CONTEN Overview. Figure 3.1 presents the clear demonstrations of proposed CONTEN architecture. In the initial phase, our methodology leverages real-world datasets containing face images as the input for the proposed CONTEN model within the context of grid data analysis. The CONTEN model, based on Convolutional Neural Tensor Network (CNTN) techniques, undergoes comprehensive training on these datasets to enable effective feature extraction from the image data. Subsequently, the process progresses to capture user images using the smart TV camera module. Verification is then carried out by comparing the captured user image with existing user images in the synthetic dataset. Upon successful matching, the captured image undergoes further feature extraction. Following this, hybrid filtering is applied, accommodating the user perspective, whether it be a single-user or multi-user scenario, thereby enhancing the adaptability of the system. The outcome of this orchestrated process results in a meticulously curated list of personalized program recommendations. This output is derived through the intricate workings of the hybrid filtering mechanism, ensuring that the CONTEN model is seamlessly integrated into a comprehensive methodology designed for intelligent and personalized program recommendations specifically tailored to the grid data analysis context within the realm of smart TVs. The root of the methodology is adapted from the study [7].

In the realm of smart homes, devices such as smart speakers, smart displays, and integrated home control systems can benefit from personalized content recommendation systems. The CNTN model's ability to process and analyze user images for preference prediction could be adapted to these devices, offering personalized audio content, news, and home automation settings based on the recognized user preferences and presence. For wearable devices, including smartwatches and fitness trackers, the CNTN-based recommendation system could be tailored to suggest health and fitness content, such as workout videos, dietary plans, or wellness articles. Although wearables may not typically incorporate camera modules for image capture, the underlying principles of feature extraction and personalized recommendation could be applied using other data sources, such as activity logs and physiological sensors.

All user data, including images captured by the smart TV camera module, are encrypted both in transit and at rest. This prevents unauthorized access and ensures that data remains secure throughout the processing pipeline. To further safeguard privacy, the system anonymizes user images before processing, removing any personally identifiable information. Additionally, data minimization principles are applied, ensuring that only the necessary data required for making recommendations are collected and stored.

3.2. Proposed CONTEN Approach.

3.2.1. Training data using CNTN. Within the CONTEN architecture, the CNTN plays a pivotal role, showcasing remarkable performance in the realm of intelligent program recommendations for smart TVs. Building upon the foundations of CNTN, CONTEN excels in training on real-world datasets, specifically those containing face images. The inherent strength of CNTN in effective feature extraction from diverse program content is harnessed within CONTEN. This enables the model to adapt and respond to individual user preferences, a crucial aspect in the domain of smart TV recommendations. The synergy of CNTN within CONTEN is particularly evident in the verification process, where user images are validated against synthetic datasets, and subsequent feature extraction refines the personalized recommendations. Method of novel CNTN is adapted from the study [15].

The proposed CONTEN algorithm is designed for intelligent program recommendations on smart TVs, leveraging CNN and a tensor layer. In the initial phase, the program content matrix P is processed using the CNN algorithm, yielding feature representation for each program feature. The input matrix P is then convolved to obtain the first layer h using the formula ($h = \tanh(b + v_q + M\,[1:r]\,.v_p$) wher b denotes the bias term, is the vector representation of the program, and $M\,[1:r]$ is a tensor. The resulting vector captures the features of the program content. Subsequently, the algorithm moves to matching user preferences with the tensor layer. The user preference vector μ and the program features vector $v_p$undergo a matching process through the tensor layer. The matching degree $s\,(\mu, p)$ is calculated using the formula $s\,(\mu, p) = \mu^t \tanh(b + v_q + N\,[1:r]\,.v_p)$representing the relevance and compatibility between user preferences and program content. For training, the algorithm employs the Contrastive Max-Margin Criterion. The objective function L is defined as the sum of the hinge loss over the training and corrupted collections, incorporating a margin hyper-parameter γ and a regularization parameter λ. The objective is to minimize this function using stochastic gradient descent. The update rule for the parameters is given by $\theta_{t,i} = \theta_{t-1,i} - \frac{p}{\sqrt{q_t}} g^2_{\tau,i}$where p is the initial learning rate, $q_t$is the accumulated squared gradient, and $g^2_{\tau,i}$is the subgradient at time step τ for parameter. This process ensures the iterative refinement of the model parameters for optimal performance in recommending personalized programs on smart

Algorithm 1 Proposed CONTEN algorithm

Input: Program content matrix $P \in R^{n_w \times l_p}$, weight matrix $M \in R^{n \times m}$, filter width m, Tensor $M[1:r] \in R^{n_s \times n_s \times r}$, parameters $V \in R^{r \times 2n},\ b \in R^r,\ \mu \in R^r$.
Apply CNN algorithm to obtain data $w_i \in R^{n_w}$ for each feature in P.
Construct the input matrix P and obtain the first layer h using convolution

$$(h = \tanh(b + v_q + M\,[1:r]\,.v_p)$$

Output the vector $h \in R^r$representing the features of the program content.
Matching the user preference with tensor layer
Input: user preference $\mu \in R^r$, program features $v_p \in R^r$
Calculate the matching degree using the tensor layer

$$s\,(\mu, p) = \mu^t \tanh(b + v_q + N\,[1:r]\,.v_p)$$

Output the matching score $s\,(\mu, p)$ representing the relevance and compatibility between user preference and program content.
Training the Contrastive Max-Margin Criterion
Input: Training collection C, corrupted collection C_0, margin hyper-parameterγ, regularization parameter λ
Define the objective function as

$$L = \sum_{(\mu,p)\in C} \sum_{(\mu,p_0)\in C_0} [\gamma - s\,((\mu, p) + s\,(\mu, p_0)] + \lambda || \ominus ||_2^2$$

Where $[x]+ = \max(0, x)$.
Minimize the objective function using stochastic gradient descent

$$\theta_{t,i} = \theta_{t-1,i} - \frac{p}{\sqrt{q_t}} g_{\tau,i}^2$$

Where p is the initial learning rate, q_t is the accumulated square gradient, and $g_{\tau,i}^2$ is the sub gradient at time step τ for parameter θ_i.

TVs.

Advanced AI and machine learning algorithms, including deep learning and reinforcement learning, can analyze viewing patterns, user interactions, and feedback in real-time to refine recommendation models continuously. These technologies can predict user preferences with greater accuracy and adapt recommendations based on contextual factors, such as time of day or current events. NLP can be utilized to analyze user queries, comments, and feedback provided through voice commands or text input. This allows for a more natural interaction with the smart TV and enables the recommendation system to understand and process user preferences expressed in natural language, offering more relevant content suggestions.

3.2.2. Hybrid filtering process. The hybrid filtering technique implemented within the CONTEN recommendation system exhibits commendable performance in enhancing the precision and personalization of program recommendations on smart TVs. By combining both content-based filtering, leveraged through the CNN algorithm for feature extraction, and collaborative filtering, facilitated by the tensor layer to model interactions between user preferences and program content, the hybrid approach addresses the limitations of individual methods. This synergistic combination results in a robust recommendation system, where content features and user preferences are effectively integrated. The method of the filtering process is adapted from the study [7].

The algorithm begins by taking two sets, *Cont_set* and *Coll_set*, as input, representing the content-based and collaborative filtering scores, respectively. The objective is to generate a top-K items set, denoted as r_k. In the first step, the algorithm initiates the process. Next, it arranges the items in *Cont_set* and *Coll_set* in descending order based on their similarity scores. Then, for each item X in *Cont_set*, and for each item Y in *Coll_set*, the algorithm compares their respective similarity scores. If the score of X is greater than the

Algorithm 2 Hybrid filtering process

Input: $Cont\_set$, $Coll\_set$
Output: top K items set, r_k
Begin
Arrange items of $Cont\_set$ and $Coll\_set$ in descending order based on the similarity score
$for\ each\ X\ \in\ Cont\_set$
$for\ each\ y\ \in\ Coll\_set$
$if(score(X)\ >\ score\ (Y))$
$r_k = r_k U_X$
else
$r_k = r_k U_Y$
$if\ size(r_k\ ==\ k)$
End

score of Y, the item X is added to the result set r_k. Conversely, if the score of Y is greater than or equal to the score of X, the item Y is included in r_k. This process continues for all items in both sets. The algorithm checks whether the size of $r_k$is equal to the desired top-K value. If so, the algorithm concludes. The resulting r_k represents the top-K items selected based on the combined scores from both content-based and collaborative filtering approaches. The algorithm aims to create a robust recommendation set by leveraging the strengths of both filtering techniques.

4. Results and Analysis.

4.1. Simulation Setup. In this section the proposed CONTEN is evaluated using the dataset of CelebA, LFW People and Synthetic dataset. This dataset is clearly illustrated in the study [7].

4.2. Evaluation Criteria. The presented Figure 4.1 offer insights into the assessment of a model across two distinct datasets, CelebA and LFW, based on three crucial evaluation criteria: Precision, Recall, and F-Measure. Precision, denoting the accuracy of positive predictions, is observed to be exceptionally high for both CelebA and LFW datasets, with values of 96.78% and 96.89%, respectively. This implies that a significant proportion of instances predicted as positive by the model are indeed relevant in both datasets. Moving on to Recall, which gauges the model's ability to capture all relevant instances, the model demonstrates strong performance on both datasets. Specifically, Recall scores of 95.48% for CelebA and 95.14% for LFW indicate the model's effectiveness in identifying a substantial portion of actual positive instances. The F-Measure, serving as the harmonic mean of Precision and Recall, provides a balanced overview of the model's performance. High F-Measure values of 96.77% for CelebA and 96.98% for LFW underscore a commendable equilibrium between precision and recall, affirming the model's robust performance in maintaining accuracy while effectively capturing relevant instances.

The training and validation accuracy trends of the proposed CONTEN model on the CelebA and LFW datasets reveal its robust learning capabilities Was shown in Figure 4.2. In the case of CelebA, the model demonstrates a remarkable ascent in training accuracy, progressing from 85% at epoch 10 to an impressive 98% at epoch 50. Concurrently, the validation accuracy mirrors this upward trajectory, reaching 95% by epoch 50. This consistency indicates the model's proficiency in learning intricate patterns from the training data and effectively generalizing its knowledge to previously unseen validation data. Similarly, for the LFW dataset, the CONTEN model showcases consistent improvement in training accuracy, achieving a commendable 96% accuracy at epoch 50. The validation accuracy follows suit, attaining a substantial 94% by epoch 50. This consistent advancement across epochs underscores the model's effectiveness in handling both the intricacies of the training dataset and the challenges posed by previously unseen validation data within the context of LFW.

In terms of training and validation loss Figure 4.2, the CONTEN model demonstrates effective error minimization during training for both CelebA and LFW. For CelebA, the training loss decreases from 0.3 at epoch 10 to a minimal 0.1 at epoch 50. Concurrently, the validation loss decreases from 0.4 to 0.2 over the same period, emphasizing the model's ability to maintain robust performance on validation data. Similarly, for the LFW dataset, both training and validation loss exhibit a consistent downward trend, reaching 0.15 and 0.25,

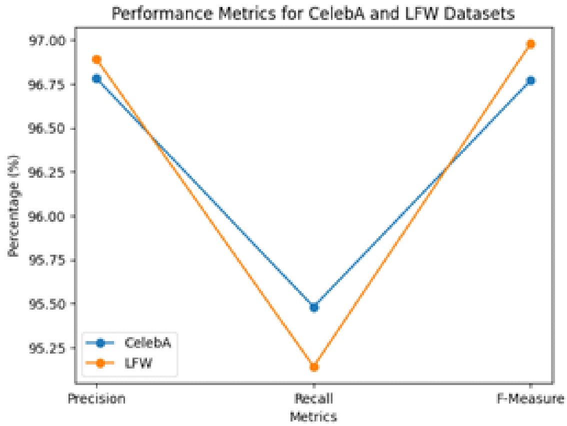

Fig. 4.1: Performance of CNTN based on datasets

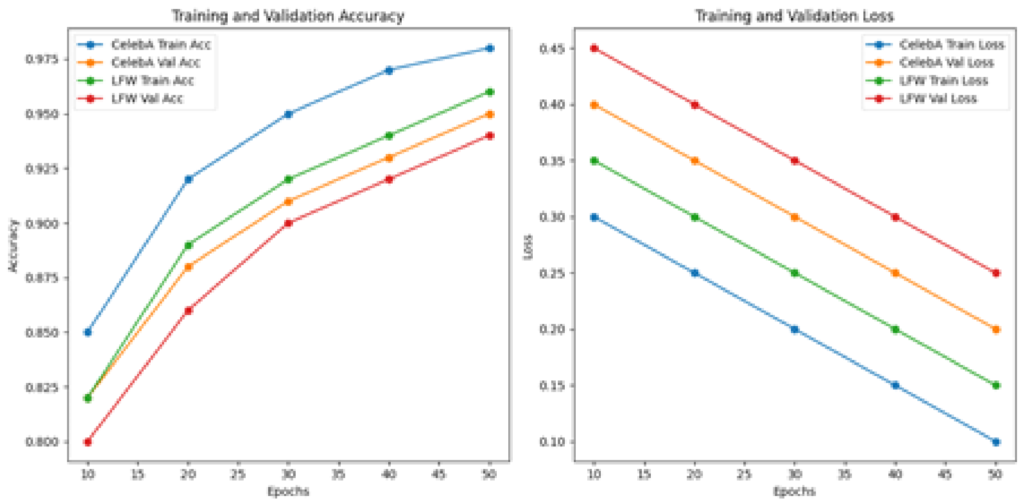

Fig. 4.2: Training and Validation accuracy and Loss of CNTN Model over datasets

respectively, at epoch 50. This downward trajectory highlights the CONTEN model's success in minimizing errors when predicting both familiar and unfamiliar data within the LFW dataset. Overall, these findings underscore the efficacy and adaptability of the proposed CONTEN model in handling diverse datasets.

4.2.1. Comparison Analysis. In this section the proposed CNTN model is compared with the Hierarchial Neural Tensor Network (HNTN), Adaptive Neural Tensor Network (ANTN), Deep Neural Tensor Network (DNTN) and Context aware Neural Tensor Network (CANTN) was demonstrated in Figure 4.3.

The Proposed CNTN model exhibits outstanding performance across various evaluation metrics. In terms of accuracy, it achieves the highest score of 0.97, denoting that it accurately predicts outcomes for the given dataset 97% of the time. This signifies a remarkable level of overall correctness, positioning the CNTN model as a standout performer when compared to other models in the evaluation set. Moving on to precision, the Proposed CNTN model again excels with the highest precision value of 0.96. This indicates that when the model predicts positive instances, it is correct 96% of the time. This high precision is particularly valuable in scenarios where false positives are costly or should be minimized, emphasizing the reliability of the CNTN

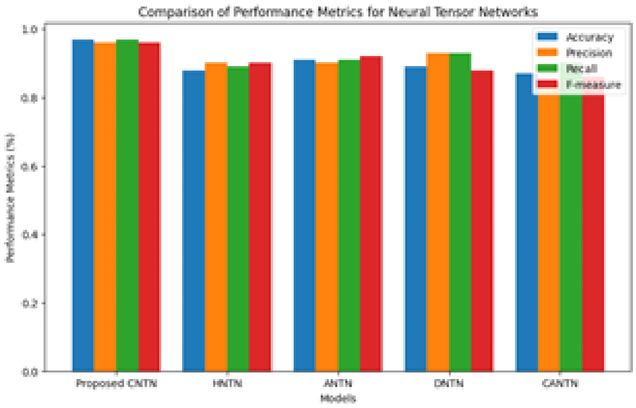

Fig. 4.3: Overall Performance comparison

model in positive predictions. Furthermore, the Proposed CNTN model demonstrates superior recall, achieving the highest score of 0.97. This signifies that the model effectively captures 97% of the actual positive instances in the dataset. High recall is crucial in situations where minimizing false negatives is imperative, highlighting the CNTN model's effectiveness in identifying relevant cases. Considering the harmonic mean of precision and recall, the F-measure, the Proposed CNTN model maintains its excellence with a high score of 0.96. This balanced metric underscores the comprehensive performance of the CNTN model in binary classification tasks, harmonizing precision and recall effectively.

5. Conclusion. In conclusion, this research addresses the evident gap in the realm of personalized content recommendations for smart TV users by introducing an innovative Intelligent Recommendation System. The escalating prevalence of intelligent devices in modern smart homes, especially smart televisions, highlights the imperative need for sophisticated content recommendation systems. Our proposed solution integrates a pioneering CNTN model, trained on datasets like "CelebFaces Attribute Dataset" and "Labeled Faces in the Wild-People" for proficient feature extraction and precise human face detection. Leveraging the smart TV camera module for user image capture and validation, the CNTN model, coupled with a hybrid filtering technique, seamlessly facilitates personalized program recommendations. The achieved training performance of approximately 97.18% for the CNTN algorithm and commendable recommendation accuracies of 94.65% for single-user scenarios and 93.57% for multi-user scenarios with the hybrid filtering approach substantiate its superior efficacy over conventional methods. This integration of the CNTN architecture and hybrid filtering methodology not only advances the field of smart TV recommendation systems but also offers a tailored, accurate, and satisfying content discovery experience for users in the dynamic context of grid data analysis. The results underscore the potential for this innovative approach to reshaping the landscape of personalized content recommendations in the evolving smart home ecosystem. Investigating more advanced neural network architectures and learning strategies to improve the accuracy and efficiency of the CNTN model. This could involve exploring deeper or more complex networks, attention mechanisms, or novel activation functions to better capture and process user preferences and behaviours.

6. Limitations and Discussions. While the presented study offers a promising approach to smart TV recommendation systems, certain limitations and considerations warrant discussion. Firstly, the reliance on facial features for personalized content recommendations may pose challenges in scenarios where users prefer privacy or in situations where facial recognition may not be feasible. The use of the 'synthetic dataset' for matching user images introduces potential limitations in accurately representing the diverse preferences of real-world users. Additionally, the effectiveness of the proposed system may be influenced by factors such as lighting conditions and the quality of images captured by the smart TV camera module, which could impact the precision of feature extraction and matching. Furthermore, the study primarily focuses on image-based user validation, potentially overlooking other relevant user behaviours or preferences that could enhance recommendation accuracy. The generalization of the proposed approach across a broader user demographic and content genres also warrants consideration. Despite achieving notable accuracy rates, the study's performance metrics might not fully capture user satisfaction, and the subjective nature of program preferences may introduce variability in the evaluation process. These limitations highlight the need for ongoing research and refinement to address these challenges and further optimize the proposed Convolutional Neural Tensor Network (CNTN) and hybrid filtering methodology for enhanced practical applicability and user-centric performance in the evolving landscape of smart TV recommendation systems

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