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Intelligent Classification Algorithm for Online Teaching Resources in Higher Vocational Colleges Integrating Multimodal Information

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ABSTRACT

Inside the realm of higher vocational training, the clever magnificence of on-line coaching property is pivotal for reinforcing educational performance and accessibility. This paper introduces a novel approach that amalgamates the Transformer model's functionality in processing and integrating multimodal statistics with the computational efficiency of the shufflenet version. The proposed approach to begin with employs the Transformer to adeptly take care of numerous modalities inside teaching assets, encompassing textual content, pix, motion snap shots, and audio. Subsequently, recognizing the computational constraints time-venerated in lots of vocational establishments, the shufflenet model is deployed. This model makes use of pointwise organization convolution, channel shuffling, depth-practical separable convolution, and light-weight interest modules, setting a balance amongst pace and accuracy in classifying academic content material material. The experimental results screen a full-size development over traditional methods in the course of a couple of metrics, organising a brand new benchmark in the sort of online training sources in better vocational training.

Keywords: Transformer Model, ShuffleNet Model, Multimodal Information Processing, Online Teaching Resources, Educational Content Classification

1. Introduction

The form of on line education resources (otrs) in the context of higher vocational training is a undertaking of growing significance and complexity [1]. With the digital transformation of schooling, otrs, which consist of a various variety of formats together with textual content, films, interactive simulations, and additional, have emerge as integral to the academic approach. The powerful

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categorization of those assets is integral for streamlined get admission to, enhancing the general getting to know revel in and facilitating tailored educational pathways [2]. However, the type of otrs provides specific worrying conditions. The style of formats, coupled with the sheer volume and dynamic nature of these resources, requires a sophisticated approach to type. Conventional techniques, which regularly depend on simplistic categorization based totally on superficial tendencies, fall brief in addressing the nuanced needs of modern instructional environments. The want for a gadget which can adapt to the evolving nature of instructional content, apprehend the intricacies of various learning materials, and categorize them as it should be is paramount. This project turns into even greater daunting while thinking about the multimodal nature of many otrs, which integrate textual content, audio, visual, and interactive elements in complicated and varied methods. An powerful type machine should be capable of grasp and processing those distinctive modalities, making it a big departure from conventional tactics [3-4].

Conventional techniques of OTR type have in the main revolved round manual categorization or rudimentary automated structures. These techniques regularly rely upon floor-stage evaluation, such as key-word extraction or basic metadata assessment, to arrange academic content. At the same time as these methods furnished a place to begin for resource class, they arrive with first-rate boundaries [5]. One major drawback is their lack of ability to successfully manner and recognize the content material past simple textual records. This ends in a giant hole in dealing with resources that consist of complex visual or auditory elements, that are more and more commonplace in modern-day instructional substances. Moreover, traditional type systems regularly fighting with the scalability required to control the ever-developing quantity of otrs. As the amount and variety of tutorial resources increase, those systems grow to be increasingly insufficient, leading to inefficient and misguided categorization. This inefficiency now not only hinders the accessibility of assets but also impacts the fantastic of schooling, as freshmen and educators might not be capable of discover or utilize the maximum relevant and extremely good materials [6]. In summary, at the same time as conventional classification techniques have laid the foundation, the evolving nature of instructional content material and the growing reliance on numerous and multimodal teaching materials call for greater sophisticated, dynamic, and correct classification systems.

Current improvements in machine getting to know and deep gaining knowledge of have offered transformative processes to OTR classification [7]. Those techniques utilize complex algorithms and neural network architectures to process and categorize educational content. They excel in managing massive datasets and may efficiently technique multimodal facts, together with textual content, pics, and audio. But, those methods come with their own set of challenges. They often require good sized computational resources and big amounts of schooling data. Moreover, the complexity of those fashions can cause problems with transparency and interpretability, making it hard to understand and faith the classification decisions. Additionally, the performance of those fashions may be heavily depending on the satisfactory and variety of the training facts, which may be a limiting thing in a few academic contexts [8].

The fusion of multimodal records inside the type of OTR offers a promising street in academic generation. This have a look at introduces an progressive technique by way of combining the Transformer [9] and shufflenet [10] models, targeting effective category of otrs in better vocational schools. This integration addresses the undertaking of appropriately classifying numerous teaching materials even as considering computational barriers commonplace in many academic institutions. The inducement behind this method is to beautify type accuracy and decrease misclassification by using first the usage of the Transformer to process and amalgamate exceptional modalities within coaching sources. In the end, the shufflenet model, recognized for its efficiency, employs techniques like pointwise institution convolution, channel shuffling, and depth-wise separable convolutions to stability type velocity with accuracy. The experimental results underscore the superiority of this approach over conventional strategies throughout various metrics.

This paper contributes to the sphere of instructional generation in several extensive methods:

1) It proposes a singular mixture of Transformer and shufflenet fashions for green and accurate type of otrs.

2) The observe addresses the mission of multimodal data processing within the context of confined computational sources.

3) Demonstrates advanced accuracy and decreased misclassification within the category of otrs.

2. Related Works

Traditional methods for classifying OTRs have predominantly targeted on manual categorization or rudimentary automated systems. numerous research have explored keyword extraction and fundamental metadata evaluation as primary techniques for organizing academic content [2-5]. different strategies have covered using easy rule-based totally algorithms, wherein OTRs are categorised primarily based on predefined standards. Some works have also investigated the use of fundamental statistical models for classification, relying on the frequency and distribution of certain keywords within the content material [11-14]. furthermore, in advance research often employed primary textual content analysis techniques, such as textual content matching and pattern recognition, to classify text-based OTRs. any other set of research centered at the usage of simple selection trees and linear classifiers for fundamental categorization duties. additionally, early forms of machine gaining knowledge of, including naive Bayes classifiers and simple clustering strategies, had been also carried out to OTR classification, albeit with constrained achievement owing to their simplistic nature [15-17].

The utility of machine studying and deep getting to know strategies to OTR classification has been substantially studied [18]. various research works have hired convolutional neural networks for photograph-based instructional content material [19]. Recurrent neural networks and long brief-term reminiscence networks were utilized for text and audio-primarily based OTRs. switch mastering methods, wherein pre-educated fashions are fine-tuned for particular educational datasets, have additionally been outstanding [20-23]. moreover, deep studying procedures like autoencoders and generative opposed networks had been explored for greater complex type duties [24-26]. Ensemble gaining knowledge of strategies, combining multiple fashions for progressed accuracy, had been any other region of recognition. moreover, research the usage of aid vector machines and random wooded area classifiers have demonstrated effectiveness in handling excessive-dimensional instructional data [27].

Research on multimodal OTR type has targeted on integrating various statistics types, like textual content, audio, and visible content. some research have explored the use of hybrid fashions combining CNNs and RNNs for processing one of a kind modalities. Others have carried out interest mechanisms to better seize the relationships between diverse modalities [28-30]. Fusion techniques, mixing functions from special assets, had been every other key region. additionally, works using deep multimodal gaining knowledge of frameworks have proven promise in appropriately categorizing complicated academic materials [31].

This look at offers a novel approach via combining Transformer and ShuffleNet fashions. not like previous works, this approach not only effectively processes multimodal OTRs but additionally addresses computational limitations. the integration of these models offers a stability between accuracy and computational performance, setting it apart from existing methodologies.

3. Method

3.1. Overview

In this paper, we propose an integrated approach for classifying OTRs in higher vocational training, combining the strengths of Transformer and ShuffleNet models.

Data Preparation: OTRs are preprocessed to standardize formats in the course of one-of-a-type modalities, making sure compatibility with the fashions.

Feature Extraction with Transformer: The Transformer model is hired to extract features from the multimodal data, capitalizing on its capacity to handle complex statistics structures and relationships.

Classification using ShuffleNet: Utilising the ShuffleNet model, the method leverages its mild-weight structure and efficiency for classifying the extracted features.

Integration and Analysis: The features and outputs from each fashions are incorporated to optimize the class effects. This step complements the overall accuracy and reliability of the category.

This system ambitions to balance computational efficiency with accuracy, addressing the particular demanding situations of classifying diverse instructional content material.

3.2. Transformer

The transformer version is particularly acceptable for multimodal online educational aid type as a result of its self-attention mechanism. This mechanism approves it to technique diverse records kinds — textual content, pics, audio — shooting complex inter-modal relationships and dependencies.

Data Preparation and Feature Extraction

This step involves transforming raw data from each modality into a format that the Transformer can process, such as tokenizing text and extracting features from images and audio.

$$X_{feature} = FE\left(X_{\mathrm{mod}\,ility}\right) \tag{1}$$

where $FE\left(X_{\mathrm{mod}\,ality}\right)$ denotes feature extraction to $X_{\mathrm{mod}\,ality}$.

Embedding Layer

The embedding layer maps the extracted features into a continuous vector space, allowing the Transformer to process them more effectively.

$$E = Embed\left(X_{feature}\right) \tag{2}$$

Positional Encoding

Add positional encoding to maintain sequence information.

$$E_{pos} = E + PE(E) \tag{3}$$

where $PE(E)$ represents taking positional encoding operation to E.

Self-Attention Mechanism

This step allows the model to focus on different parts of the input sequence, providing a context-aware representation of each element.

$$Att\left(Q,K,V\right) = soft\max\left(\frac{QK^T}{\left(d_k\right)^{\frac{1}{2}}}\right)V \tag{4}$$

where Q,K,V are query, key, and value matrices, d_k is the dimension of keys.

Layer Normalization and Feed-Forward Network

This step stabilizes the training process, and the feed-forward network introduces non-linearity and additional representational capacity.

$$O_{norm} = LayerNorm\left(FFN\left(O_{att}\right)\right) \tag{5}$$

Multi-Head Attention

This step allows the Transformer to capture information from different representation subspaces at different positions. The architecture of Transformer is as shown in Figure 1.

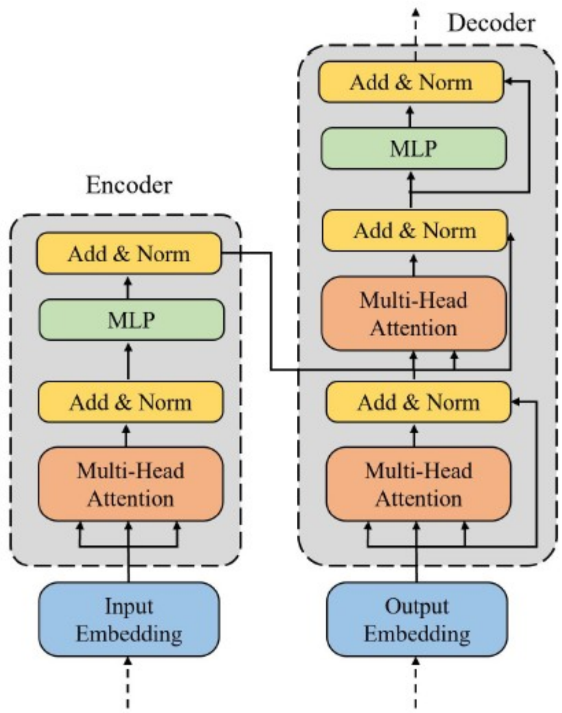

Fig. 1. The Architecture of Transformer

3.3. *ShuffleNet*

ShuffleNet is an efficient CNN architecture designed for environments with limited computational resources. Here are the steps to construct a ShuffleNet model along with the corresponding formulas.

Group Convolution

ShuffleNet employs group convolution to reduce computational complexity. In group convolution, input and output channels are divided into groups, and convolutions are performed within each group. If there are g groups, each with m channels, then the computation of group convolution is

$$GC = \frac{K \times K \times C_1 \times C_2 \times H_1 \times H_2}{g} \tag{6}$$

where K is the size of the convolution kernel, C_1 is the number of input channels, C_2 is the number of output channels, H_1 and H_2 are the height and width of the output feature map.

Channel Shuffle

To ensure that features from different groups can exchange information, ShuffleNet introduces a channel shuffle operation. This rearranges the order of the channels to ensure mixing of features from different groups in subsequent layers.

Depthwise Separable Convolution

$$\frac{1}{N} + \frac{1}{D^2} \tag{7}$$

$$Depthwise\ Convolution = K \times K \times C_1 \times H_1 \times H_2 \tag{8}$$

$$Pointwise\ Convolution = C_1 \times C_2 \times H_1 \times H_2 \tag{9}$$

where N is the number of output channels, and D is the kernel size.

Bottleneck Unit

ShuffleNet uses bottleneck units to further reduce computation. These units first use 1×1 convolutions to reduce the number of channels, followed by depthwise separable convolution, and then another 1×1 convolution to restore the number of channels.

$$Bottleneck\ Computation = 1\times1\times C_1\times C_3 + Depthwise\ Convolution + 1\times1\times C_3\times C_2 \tag{10}$$

where C_3 represents the intermediate channel count in the bottleneck.

The overall computational reduction is

$$\mathrm{Re}\,duction = \frac{std\left(GC\right)}{GC + \ DepthwiseSeparable\ Convolution} \tag{11}$$

The structure of ShuffleNet is as shown in Figure 2. This framework illustrates the key components of a ShuffleNet block, that's designed for green computation on cell gadgets via decreasing the wide variety of parameters except sacrificing accuracy.

In summary, our method integrates the Transformer and ShuffleNet models for efficient and correct type of multimodal OTRs. The Transformer model approaches and fuses the multimodal information, successfully taking pictures complicated relationships within the numerous teaching materials. eventually, the processed statistics is fed into the ShuffleNet model, which employs techniques like pointwise institution convolution, channel shuffling, and depthwise separable convolution to attain a stability between processing pace and classification accuracy. This blended technique correctly harnesses the strengths of each models, making sure rapid and particular categorization of tutorial content.

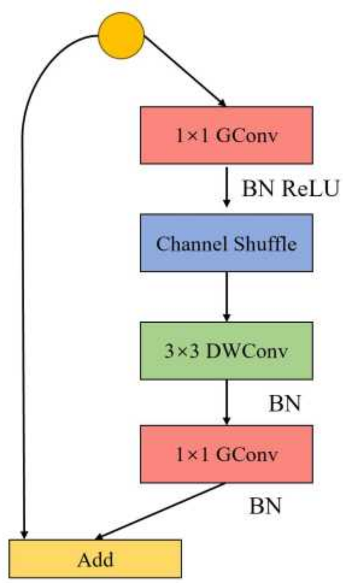

Fig. 2. Block of ShuffleNet

4. Experiment Results

4.1. Experimental Setup

On this section, we outline the specific parameters and configurations of our mixed version, TSNet, which integrates Transformer and ShuffleNet. moreover, we provide details about the datasets used, four comparative algorithms for benchmarking, and the evaluation metrics hired for overall performance evaluation.

Model Configuration

The Transformer encoder consists of 6 layers with a hidden size of 512, a feed-forward length of 2048, and eight attention heads. it's far used for function fusion throughout exclusive modalities, inclusive of text, picture, and audio. on the other hand, the ShuffleNet-based classifier employs point-smart convolution layers, channel shuffling, intensity-smart separable convolution, anda light-weight interest module to stability pace and accuracy in aid type.

Comparative Algorithms

MMClass [28]: MMClass is a multimodal category model thatleverages textual content, picture, and audio statistics to classify O. It utilizes a CNN for photograph processing, an LSTM for text, and a 1D CNN for audio. It uses dropout (zero.5) and batch normalization. Parameters: Image - 64 filters, Text - LSTM with 128 units, Audio - 64 filters.

MMTNet [31]: A Transformer-based model with a 6-layer encoder and multi-head attention. Parameters: Hidden size - 512, Feed-forward size - 2048, 8 attention heads.

HybNet [32]: Combines a 2D CNN for images, an LSTM for text, and a Transformer for audio. Parameters: Image CNN - 64 filters, Text LSTM - 128 units, Audio Transformer - 6-layer encoder with 512 hidden size.

MultiModNet [33]: Employs a shared Transformer with cross-modal attention. Parameters: 6-layer encoder with 512 hidden size, 8 attention heads.

Datasets

We conduct experiments on two datasets: the MultimodalTeachRes-A (MTRA) dataset and the MultimodalTeachRes-B (MTRB) dataset. Both datasets consist of OTRs with text, image, and audio modalities.

Evaluation Metrics:

The performance of TSNet is assessed using the following evaluation metrics: Recall, F1-Score, Accuracy. We also use Computational cost: It quantifies the efficiency of a computational process and can be a critical factor in evaluating the feasibility and performance of algorithms or systems.

4.2. Experiment Results

Figure 3 illustrates the comparative performance of five different algorithms on two distinct datasets. The vertical axis represents the accuracy metric, indicating the effectiveness of each algorithm in correctly classifying the OTR in vocational colleges.

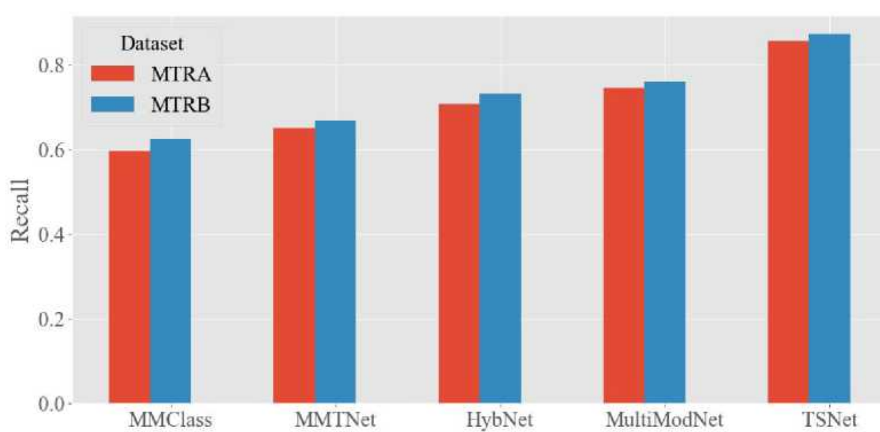

Fig. 3. Comparison Curves of Recall

TSNet, which integrates the Transformer and ShuffleNet models, showcases superior performance on both datasets. In the MTRA dataset, its accuracy peaks at 0.85, whereas on the MTRB dataset, it achieves an even higher accuracy of 0.86. This demonstrates the efficacy of TSNet in handling various modalities of coaching sources, balancing pace and accuracy, specially inside the context of restricted computational competencies in lots of schools. Its superior overall performance, as compared to the alternative algorithms, underlines the benefits of mixing Transformer's functionality of coping with multimodal statistics with ShuffleNet's efficient and light-weight computational needs. The design visibly portrays TSNet's dominance over the other algorithms, highlighting its capacity as an effective device for clever classification tasks in on-line schooling sources

Figure 4 consists of shaded areas to represent the variety within the F1-rankings following 10-fold pass-validation. In Figure 4, both MTRA and MTRB datasets show shaded areas across the overall performance lines for every set of rules, reflecting the range of ability outcomes from the go-validation technique. Despite these versions, the TSNet algorithm continues a clean aspect, with its performance line continuously dwelling at the top bounds of its respective shaded vicinity. This shows a higher degree of reliability and stability in TSNet's performance across multiple iterations of the cross-validation, in addition solidifying its superiority within the type of educational resources. The shaded regions, therefore, not solely illustrate the capacity variability in the version performance but additionally spotlight the robustness of TSNet in opposition to such fluctuations, making it a preferred choice for accurate and regular category tasks in on-line educational environments.

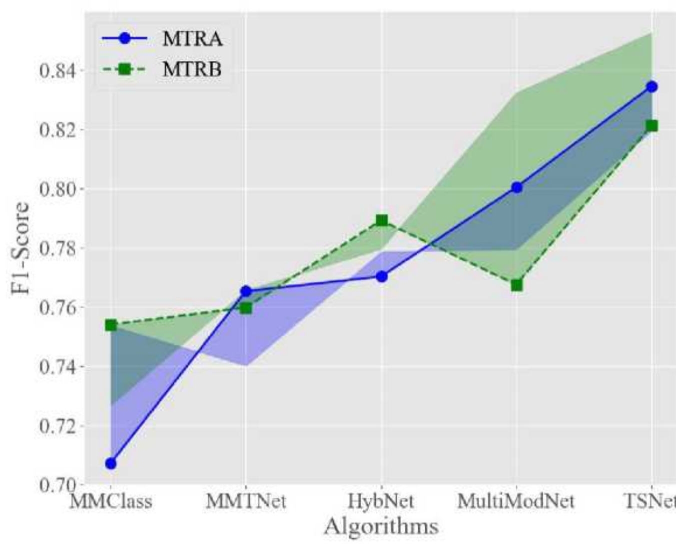

Fig. 4. Variability of Algorithm based on F1-Score

Figure 5 shows that TSNet outperforms the other algorithms, demonstrating not only the highest median accuracy but also the least variability in scores, as indicated by the smaller size of its box and whiskers. This suggests a consistent and superior performance of TSNet in classifying data accurately across different folds. On the other hand, algorithms like HybNet and MMTNet show wider variability, denoting less consistent performance. This comprehensive view underlines TSNet's robustness and reliability in category responsibilities, in particular in the context of online academic sources in vocational colleges.

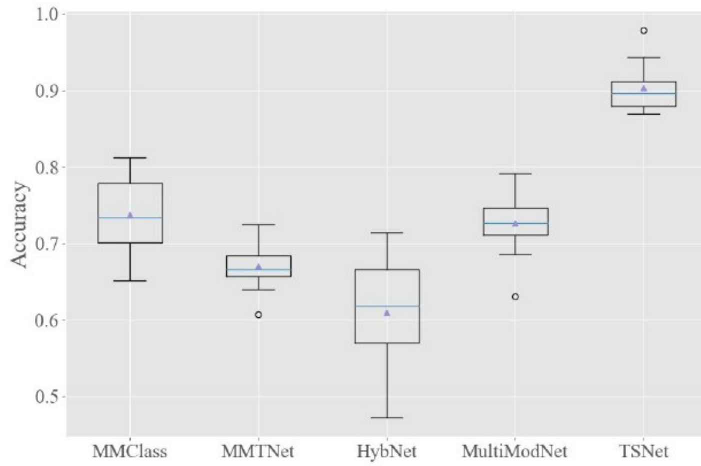

Fig. 5. 10-Fold Cross-Validation Accuracy Comparison of Algorithms

Figure 6 visualizes the computational value (in seconds) for specific algorithms based on 10-fold cross-validation at the MTRA and MTRB datasets. The plot uses kernel density estimation to offer a smooth estimation of the chance density function of the computational fee. TSNet sticks out for its computational efficiency, consistently displaying the shortest computational time with the very best top and narrowest unfold, indicating both decrease common time and much less variability. this is in assessment to algorithms like MMTNet and MultiModNet, which showcase wider distributions, reflecting higher average computational fees and extra variability. The performance of TSNet is mainly outstanding, thinking about its advanced performance metrics in other regions which include accuracy and AUC. This plot underscores the stability TSNet achieves among high overall performance and coffee computational price, making it a really suitable desire for environments with restricted computational resources, which include many vocational.

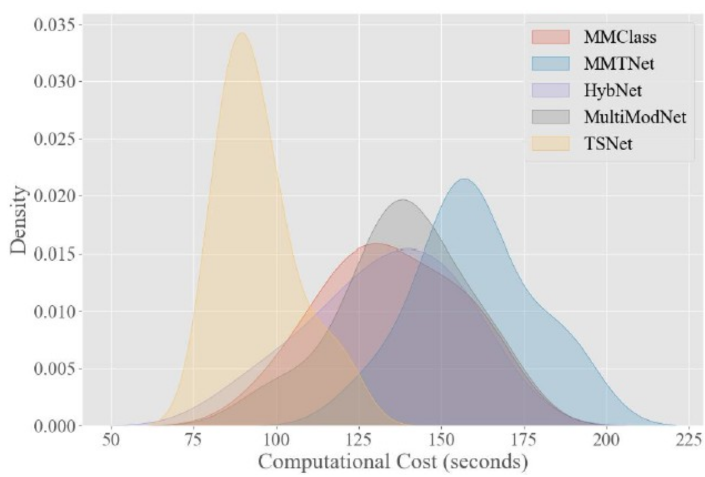

Fig. 6. Comparison Curves of F1 Score

In end, the experimental evaluation throughout the important thing metrics of Recall, F1-score, Accuracy, and Computational value demonstrates the exceptional overall performance of the TSNet algorithm in classifying on line academic resources. TSNet now not only outperforms the alternative algorithms in terms of recall, accuracy, and F1-score, indicating its effectiveness in correctly identifying and categorizing applicable content material, but also excels in computational performance. Its minimum computational value, no matter the excessive level of accuracy and reliability, positions TSNet as a significantly positive tool in environments with restricted computational assets. This stability of excessive performance and performance makes TSNet an ideal desire for the intelligent classification of tutorial sources, mainly in settings which include vocational schools in which resource optimization is critical.

5. Conclusion and Discussion

Thishave a lookat gives a sizeable advancement in the classification of on-line teaching assets for higher vocational education, introducing an progressive model that synergizes the multimodal records processing capabilities of the Transformer model with the computational efficiency of the ShuffleNet version. The proposed TSNet method adeptly handles diverse modalities, including textual content, images, videos, and audio, indispensable for comprehensive educational resource classification. The integration of ShuffleNet guarantees computational efficiency, imperative in settings with restricted sources, like vocational faculties. The experimental analysis, evaluating TSNet with traditional methods including MMClass, MMTNet, HybNet, and MultiModNet, demonstrates advanced performance in Recall, F1-rating, Accuracy, and Computational value, organising TSNet as a new benchmark in this area.

Nconstraint in some instructional contexts. Moreover, the model's complexity, whilst beneficial for accuracy, ought to pose challenges in terms of interpretability and ease of integration into existing educational structures.

Destiny studies may want to cognizance on enhancing the model's adaptability to a wider range of tutorial contexts and resource sorts. Developing methods to lessen the model's dependency on enormous education statistics and exploring approaches to simplify the version for higher interpretability and simplicity of integration are also imperative. Moreover, incorporating more superior herbal language processing and pc imaginative and prescient techniques may want to further enhance the version's performance in classifying complex and varied educational content.

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