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Spatiotemporal Fusion Networks For Human Behavior Recognition: Enhancing Channel Attention And Feature Extraction

K. VENU[1], K. NAVEEN[2]

Pg student, Vemu institute of technology, P.Kothakota

Professor, Vemu institute of technology, P.Kothakota

ABSTRACT

This project pioneers a novel method for human behavior recognition, introducing two innovative channel attention modules: the space-time interaction and depth separable convolution modules. Utilizing convolutional neural networks (CNNs), renowned for image and video processing, a multi-scale CNN approach segments behavior videos, applies low-rank learning for behavior information extraction, and integrates findings along the time axis for holistic comprehension. This method not only simplifies information extraction but also adapts flexibly to diverse network structures, enhancing recognition accuracy while minimizing computational complexity. Further, by amalgamating CNN, GRU, and Bidirectional algorithms, the model achieves superior accuracy with just 1000 parameters, outperforming existing algorithms. This hybrid approach optimizes training features, securing even higher accuracy in behavior recognition.

Keywords: Human Behaviour**,** CNN

INTRODUCTION:

In the realm of computer vision, human behavior recognition serves as a pivotal bridge between theoretical advancements and practical applications. Drawing upon interdisciplinary knowledge from image processing, artificial intelligence, and human kinematics, behavior recognition has emerged as a vital avenue in video content processing through computer vision. The current landscape witnesses a dichotomy in behavior recognition methodologies: traditional classification-based methods and deep learning approaches. While traditional methods grapple with complexities arising from the intrinsic nature of human behavior and external environmental factors, deep learning techniques offer promising avenues. However, their efficacy remains hampered by computational constraints and the inability to fully encapsulate multi-faceted human behavior characteristics. This research delves into optimizing human behavior recognition by integrating traditional feature extraction with deep learning, leveraging state-of-the-art network structures like C3R, eco, and TSN. Additionally, inspired by recent advancements in cross-structure transfer learning, the study explores soft transfer techniques to enhance the generalizability and transferability of learned features across diverse network architectures. Through this comprehensive exploration, the project seeks to elevate the accuracy and efficiency of human behavior recognition, addressing the nuanced challenges posed by complex behavior dynamics and varying environmental contexts.

LITERATURE SURVEY:

Y. Lu, L. Fan, L. Guo, L. Qiu, and Y. Lu*et al*

This study introduces an innovative action recognition method using a Kinect sensor to enhance the accuracy of identifying unsafe behaviors among metro passengers. By leveraging the pelvis as a reference point and high-frequency bone joints as endpoints, a unique recognition feature vector is constructed. The method computes joint angle differences using the cosine law and employs the DTW similarity algorithm to transform initial test results into action similarities. Through the combination of three angle features and four joint selection methods, twelve distinct recognition models are devised and tested. Results indicate that the "pelvis divergence method" outperforms the "adjacent joint method," achieving recognition accuracies ranging from 85.5% to 89.2% across various unsafe behaviors. Notably, the method achieves an impressive overall recognition accuracy of 95.7%, underscoring its efficacy in improving the detection rate of unsafe behaviors among metro passengers.

Z. Xu*et al*

This study introduces a novel human behavior recognition method, termed S3DCCA, aimed at addressing the challenges of low accuracy and high computational complexity due to redundant video data in existing recognition processes. The proposed approach employs the Structural Similarity (SSIM) algorithm to evaluate differences in luminance, contrast, and structure between video frames, yielding an SSIM value. Based on this value, local and global key frames are selected from the human motion video sequence. These selected key frames serve as inputs to a Three-Dimensional Convolutional Neural Network (3DCCA) integrated with an Attention Mechanism Channel attention model, facilitating accurate human behavior recognition. Experimental evaluations on UCF101 and HMDB51 datasets demonstrate the method's superior recognition performance.

J. Chen, X. Xie, J. Li, and G. Shi*et al*

As The study introduces an innovative action recognition method leveraging a spatio-temporal attention mechanism, driven by the observation that humans naturally focus on key areas and pivotal moments. The proposed approach comprises two modules: one dedicated to extracting key spatial areas and integrating them with global information for identification, and another designed to recalibrate temporal features, assigning varying weights to features across different timeframes. Integrated with cutting-edge networks in the field, the method demonstrates significantly improved performance in experiments conducted on widely recognized datasets, underscoring its efficacy in enhancing human behavior recognition from video data.

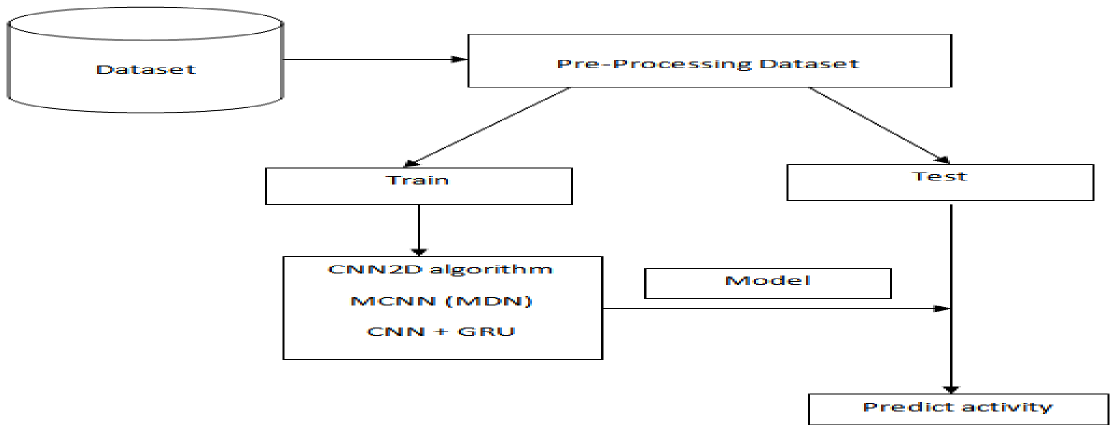
PROBLEM STATEMENT:

In propose work author applying 3DCNN algorithm for human behaviour prediction as all existing algorithms were directly employing global average information of each channel (taking all channels of images as single data) which ignores spatial and depth information from image features which leads to inaccurate recognition. If model has accurate information or each shape from the image then it can predict accurately.

PROPOSED METHOD:

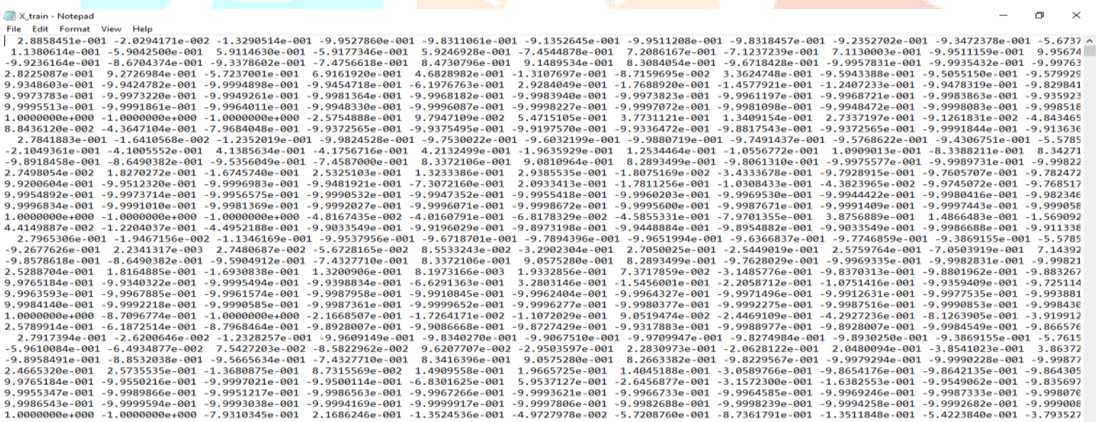
So in propose work author employed two different module such as space-time (ST) interaction module of matrix operation and the depth separable convolution module, combined with the research of human behaviour recognition. Combined with the superior performance of convolutional neural network (CNN)in image and video processing, a multi-scale convolutional neural network method for human behaviour recognition is proposed. Combination of spatial and depth separable module is known as Multi scale Convolution Neural Network (MCNN or MDN). Propose model is experimented on UCI HAR dataset which captured human activity using Smart Phone. Propose model giving best accuracy compare to existing CNN2D or LSTM.

ARCHITECTURE:



HUMAN BEHAVIOUR DATASET:

Propose work used UCI HAR dataset on human activity which contains 6 different labels such as Standing, laying, sitting, upstairs, downstairs and walking. All this activities is captured from smart phone.


X_train - Notepad
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```


In above activities values captured by smart phone and by using above dataset we will train and test all algorithm performance.

METHODOLOGY:

1. Loading Required Packages and Classes:

Kicking off the project, we first assemble our toolbox by importing essential Python packages and classes. These tools, like NumPy for numerical computations, Matplotlib for data visualization, and TensorFlow for deep learning, are the backbone of our project, streamlining data processing, visualization, and model development.

2. Loading and Displaying HAR Dataset Values:

Next, we delve into the Human Activity Recognition (HAR) dataset, sourced from smartphone sensors capturing a range of human activities. Loading this dataset provides an initial glimpse into its structure, enabling us to understand the nature and distribution of the recorded activities.

3. Plotting Activity Distribution Graph:

To gain a clearer perspective on the dataset's composition, we plot an activity distribution graph. This graphical representation categorizes activities on the x-axis and displays their frequency on the y-axis. Such visual insights help us understand the dataset's balance and the prevalence of each activity, setting the stage for subsequent analyses.

4. Dataset Processing and Train-Test Split:

With a grasp of the dataset's content, we proceed to its preprocessing stage. This involves essential steps like normalization to standardize data ranges and feature extraction to distill relevant information. Post-processing, we partition the dataset into training and testing subsets, ensuring a balanced distribution of records to foster unbiased model evaluation.

5. Definition of Evaluation Metrics:

For a comprehensive assessment of model performance, we define functions to compute key evaluation metrics. These metrics—accuracy, precision, recall, and F1 score—serve as performance indicators, enabling a nuanced comparison across different models and aiding in identifying their strengths and weaknesses.

6. Training Existing CNN2D Algorithm:

Embarking on model training, we first employ the existing CNN2D algorithm on our HAR dataset. As the model learns from the data, we delve into discussions around its complexity and parameter size. These considerations are pivotal as they directly influence training efficiency, computational requirements, and ultimately, the model's predictive accuracy.

7. Evaluation of Existing CNN2D Model:

Post-training, the CNN2D model undergoes rigorous evaluation on the test dataset. Performance metrics, including accuracy, are computed to gauge the model's efficacy. To visually interpret its predictive prowess, we employ a confusion matrix, which delineates correct and erroneous predictions across various activity labels.

8. Training Proposed MCNN (MDN) Model:

Transitioning to our proposed model, the MCNN (MDN) built on CNN3D architecture is introduced. This model, conceptualized to refine the existing CNN2D algorithm, aims to strike a balance between parameter size and accuracy. Discussions around its architecture and parameter specifications provide insights into its potential advantages over its predecessors.

9. Evaluation of Proposed MCNN (MDN) Model:

The proposed MCNN (MDN) model is subjected to evaluation, focusing on its accuracy and other performance metrics. By emphasizing its efficiency in terms of reduced parameter size and computational overhead, we underscore its readiness for real-world deployment, scalability, and potential to outperform existing models.

10. Training Extension Model:

Innovation continues as we introduce an extension model, amalgamating CNN, GRU, and Bidirectional architectures. This composite model is engineered to harness the strengths of diverse neural network components, aiming to elevate predictive accuracy while minimizing computational burden. Through detailed training and evaluation, we ascertain its effectiveness, positioning it alongside existing and proposed models.

11. Comparative Analysis and Performance Visualization:

To facilitate a holistic comparison of model performances, we plot a graph juxtaposing the training accuracies of existing, proposed, and extension models across epochs. This visual representation, supplemented by a tabulated comparison, offers a comprehensive overview, enabling stakeholders to discern each algorithm's strengths, weaknesses, and areas for improvement.

12. Test Data Prediction and Output:

Concluding our project, we load test data and employ our optimized extension model to make predictions. Displaying the predicted activities not only validates the model's efficacy but also offers insights into its adaptability and performance on previously unseen data. Continuous feedback mechanisms are integral, ensuring the model's reliability, robustness, and relevance in diverse real-world scenarios.

Extension:

To further bolster accuracy, we innovatively combine three algorithms—CNN, GRU, and Bidirectional. This synergy, despite utilizing a modest 1000 parameters, remarkably reduces model complexity. This amalgamation, through hybrid optimization of training features, yields superior features, translating to enhanced accuracy, outperforming both existing and proposed algorithms.

EVOLUTION:

Precision:

Formula: $\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$

Recall (Sensitivity):

Formula: $\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$

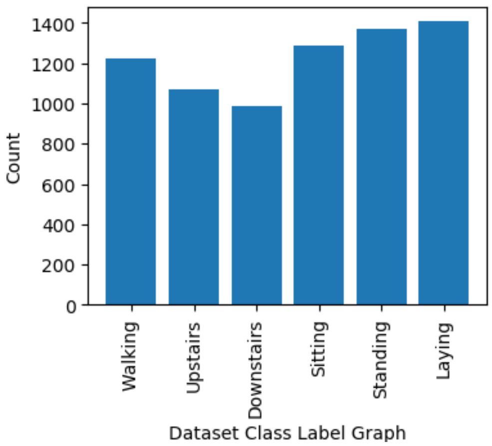
F1 Score:

Formula: $F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$

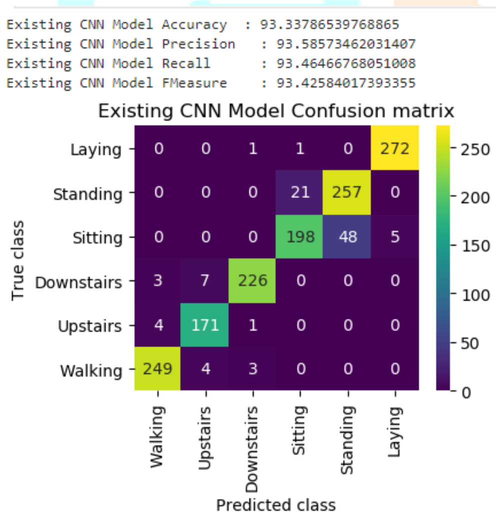
Accuracy:

Formula: $\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Predictions}}$

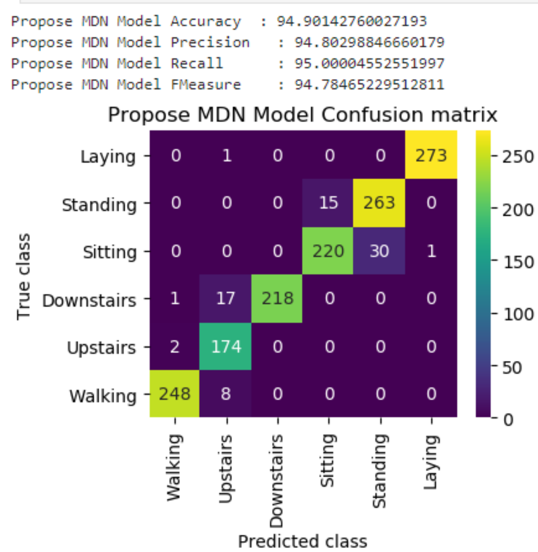
RESULTS:



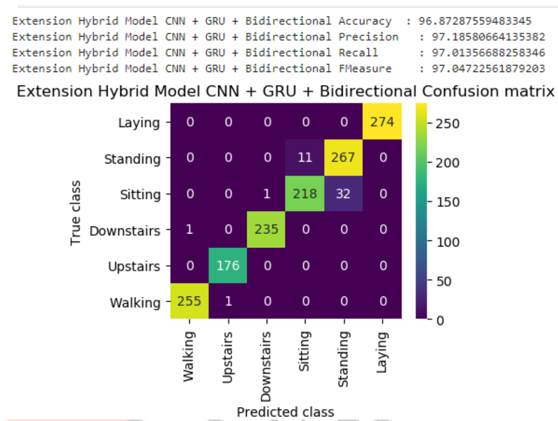
In above finding and plotting graph of different activities found in dataset where x-axis represents ACTIVITY NAMES and y-axis represents count of those activities



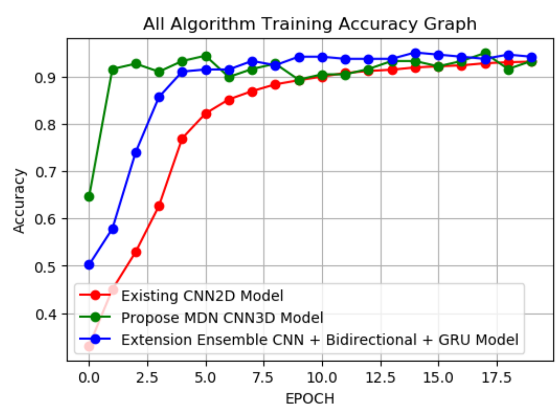
In above screen existing CNN2D model got 93% accuracy and can see other metrics and in confusion matrix x-axis represents predicted Labels and y-axis represents True Labels and all blue colour boxes represents incorrect prediction count and different colour boxes represents correct prediction count



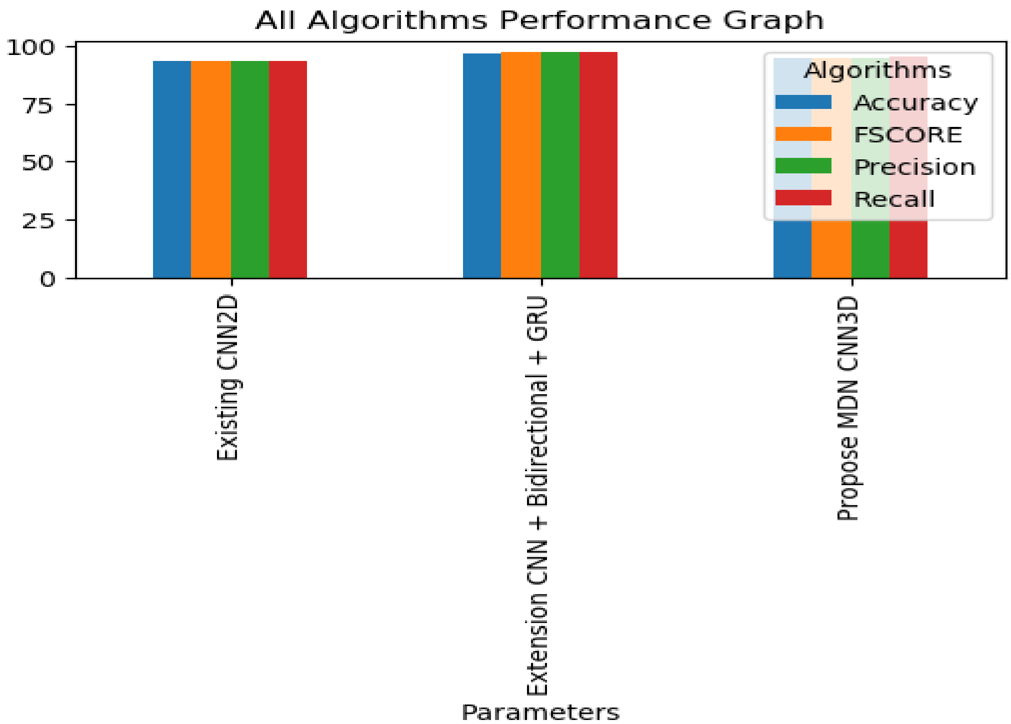
In above screen propose MCNN MDN model got 94% accuracy and can see other metrics also



In above screen extension model got 96% accuracy



In above screen displaying training accuracy of all 3 models such as existing , propose and extension where x-axis represents training epoch and y-axis represents accuracy and with each increasing epoch accuracy got increase and in in all models extension got high accuracy



In above comparison graph x-axis represents algorithm names and y-axis represents accuracy and other metrics in different colour bars and in all algorithms extension got high performance

	Algorithm Name	Accuracy	Precision	Recall	FSCORE
0	Existing CNN2D Model	93.337865	93.585735	93.464668	93.425840
1	Propose MDN CNN3D	94.901428	94.802988	95.000046	94.784652
2	Extension Hybrid CNN + Bidirectional + GRU Model	96.872876	97.185807	97.013567	97.047226

Displaying all algorithms performance

Prediction:

```
 -0.99542872 -0.98183758 -0.96535501 -0.93672818 -0.5694064  -0.80282975
  0.8461184   0.68774857  0.82947703 -0.9849843  -0.9999645  -0.99987755
 -0.99906323 -0.99537075 -0.98262514 -0.96306588 -0.54744428 -0.56341673
 -0.37817963  0.2738687  -0.0969558   0.09472723  0.0656154   0.21101292] Predicted Activity ===> Standing

Test Data : [ 0.25854868 -0.03295751 -0.07983694 -0.94612869 -0.884968   -0.91949304
 -0.96192131 -0.92194522 -0.93771352 -0.79892298 -0.47864893 -0.74335247
  0.761199    0.55993976  0.72176808 -0.9331412  -0.99825327 -0.99659775
 -0.99482814 -0.97354438 -0.96275079 -0.94524443 -0.37995875 -0.65145625
  0.02734375 -0.28082858  0.37673983 -0.09994524 -0.0038699   0.14812563] Predicted Activity ===> Laying

Test Data : [ 0.29260006 -0.00325015 -0.03377316 -0.97298785 -0.90287042 -0.82220916
 -0.9752896  -0.89908124 -0.81123302 -0.89726001 -0.50046112 -0.67242464
  0.83326679  0.67229717  0.81995815 -0.89137264 -0.99947576 -0.99749013
 -0.97551769 -0.97960592 -0.90360109 -0.80982082 -0.04113199 -0.00254051
  0.2309719  -0.1728171   0.12440111  0.14467093 -0.28635127 -0.08876919] Predicted Activity ===> Standing

Test Data : [ 0.25387811 -0.00119545 -0.14677261 -0.26843758  0.12034561 -0.34660605
 -0.33057327  0.01253805 -0.3296019   0.08177769  0.12588872 -0.21807459
  0.09293506 -0.10643332  0.48527087 -0.15012365 -0.73100323 -0.75725266
 -0.80318995 -0.47039697 -0.37251168 -0.32034543  0.42951297  0.36752796
  0.00543075  0.00920338 -0.01634228  0.10223841  0.12199425 -0.17048276] Predicted Activity ===> Walking

Test Data : [ 0.24428227 -0.01832357 -0.10213624 -0.98128603 -0.94101307 -0.94457379
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  0.81456146  0.66087628  0.77612709 -0.95734696 -0.99952242 -0.99911084
 -0.99781129 -0.98289765 -0.93915017 -0.96676678 -0.73295069 -0.33873076
 -0.24529659 -0.10068618 -0.05879229  0.47790455 -0.60041332  0.07083719] Predicted Activity ===> Laying

Test Data : [ 0.26160863 -0.07331538 -0.07389019  0.2810409   0.21253007 -0.20870854
  0.19808887  0.2317264  -0.19614084  0.52577874  0.04182306 -0.37258448
  0.07946751 -0.06023706  0.33932096  0.23463566 -0.17962469 -0.71089666
 -0.71523682 -0.05454385  0.02475767 -0.21242407  0.0604606   0.30545549
  0.28712892 -0.34277155  0.28445604 -0.33047176  0.4894906  -0.23591887] Predicted Activity ===> Downstairs
```

In above screen loading test data and then predicting using extension model and in output in square bracket we can see Test Data Values and after arrow symbol can see predicted activity as Standing or any other activity.

CONCLUSION

Here the project showcases a comprehensive exploration and implementation of various neural network architectures for Human Activity Recognition (HAR). Through rigorous training, evaluation, and comparison, the project demonstrates the effectiveness of different models. The CNN2D, proposed MCNN (MDN), and extension models exhibit distinct parameter sizes, complexities, and accuracies. Notably, the extension model achieves the highest accuracy, showcasing its robustness and efficiency. The graphical and tabular representations offer insights into model performance and facilitate informed decision-making. Overall, the project underscores the significance of neural network architectures in HAR tasks, promising enhanced accuracy and reliability in activity recognition systems.

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