

**PERFORMANCE ANALYSIS OF DEEP LEARNING ALGORITHMS  
FOR HUMAN ACTION RECOGNITION USING SPATIO  
TEMPORAL FEATURES FROM VIDEO IMAGES**

Thesis submitted to Bharathiar University  
in partial fulfillment of the requirements for the award of the Degree of  
**DOCTOR OF PHILOSOPHY IN COMPUTER SCIENCE**

By

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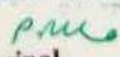
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2. Srilakshmi, N., & Radha, N. (2021). Deep Positional Attention-based Bidirectional RNN with 3D Convolutional Video Descriptors for Human Action Recognition, IOP Conference Series: Materials Science Engineering. 1022 012017 (SCOPUS INDEXED)
3. Srilakshmi Nagarathinam<sup>1\*</sup> Radha Narayanan. (2022). Deep Positional Attention-Based Hierarchical Bidirectional RNN with CNN Based Video Descriptors for Human Action Recognition., International Journal of Intelligent Engineering and Systems, Vol.15, No.3, DOI: 10.22266/ijies2022.0630.34 (SCOPUS INDEXED)
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## LIST OF ABBREVIATION

1D-CNN	1-D convolutional neural networks
2T-GCN	Two-task graph convolutional network
3D	Three dimensions
3D-CNN	3D deep Convolutional Neural Network
AAL	Ambient Assisted Living
AMC-CNN	A multi-channel convolutional neural network
Bi-GRU	Bidirectional-Gated Recurrent Unit
BLSTM	Bidirectional long short-term memory
BPAN	Bilinear Pooling and Attention Network
BRNN	Bidirectional Recurrent Neural Network
C2LSTM	Correlational Convolutional LSTM
C3D	Convolutional 3D network
CGFA	Convolution Gated Fusion Algorithm
CMFA	Convolution Memory Fusion Algorithm
CNN-IMU	CNN- inertial measurement unit
CNN-LSTM	convolutional neural network long short-term memory network
CNNs	Convolutional Neural Networks
CRFs	Conditional Random Fields
CSI	Channel State Information
DAML	Deep Appearance and Motion Learning
DCNN	Deep Convolutional Neural Network
DFT	Discrete Fourier Transform
Dis	Dynamic Images
DL	Deep Learning

DNN	Deep Neural Network
DRNN	deep recurrent neural networks
E2EDLF	End-To-End Deep Learning Framework
EE	Energy Expenditure
ELM	Extreme Learning Machine
EMOD	Efficient motion detection
FCL	Fully Connected Layer
FCN	Fully Convolutional Network
FN	False Negative
FP	False Positive
GAF	Gramian angular field
GCN	Graph Convolutional Network
GMM	Gaussian Mixture Model
GPS	Global Positioning System
GRU	Gated recurrent units
HAR	Human Action Recognition
HCI	Human-Computer Interaction
HHIs	Human-to-Human Interactions
HLA	Hybrid Learning Algorithms
HMM	Hidden Markov model
HOG	Histogram of Gradient
HSMM	Hidden Semi-Markov Models
Hyper-GNN	Hyper-Graph Neural network
ICA	Independent Components Analysis
JCA	joint-wise channel attention

JDD	Joints-pooled 3D-Deep Convolutional Descriptors
JTDD	Joints and Trajectory-pooled 3D-Deep Convolutional Descriptor
JTDGPAHBRD	JTD-Geometric and PAHBRD
JTDGPAHBRD-GCN	Graph Convolutional Network with the Joints and Trajectory-pooled 3D-Deep Positional Attention -based Hierarchical Bidirectional Recurrent Convolutional Descriptors
JTDPAHBRD	Joints and Trajectory-pooled 3D-Deep Positional Attention -based Hierarchical Bidirectional Recurrent Convolutional Descriptors
JTPADBRD	Joints and Trajectory-pooled 3D-Deep Positional Attention-based Bidirectional Recurrent Convolutional Descriptor
KF	Kalman Filter
LCRF	Linear Conditional Random Field
LL	Left Leg
LR	Left Arm
LSTM	Long Short-Term Memory
Mdk-ResNet	multi-dilated kernel residual
METs	Metabolic Equivalents
ML	Machine Learning
MLP	multilayer-perceptron
MRDGCN	Manifold Regularized Dynamic Graph Convolutional Network
NB	Naive Bayes
PA	Physical Activity
PAD	Penn Action Data Set
PABRNN	Positional Attention-based Bidirectional Recurrent Neural Network



PABRNN	PA-Bidirectional RNN
PAHBRNN	Positional Attention-based Hierarchical BRNN
PCA	Principal Component Analysis
RA	Right Arm
Res-Bidir-LSTM	Residual-Bidirectional-LSTM
RFID	Radio frequency identification
RFIG	Recognize Fluid Intake Gestures
RL	Right Leg
RNN	Recurrent Neural Network
SEMN	Skeleton Edge Motion Networks
SGP	structure-based graph pooling
SPI	Skeletal Pose Image
SRU	Simple recurrent units
STDDCN	Spatio-Temporal Distilled Dense-Connectivity Network
STSIs	Skeletal Trajectory Shape Images
SVM	Support vector machine
Sybio-GNN	Symbiotic GNN
TD	Temporal Dropout
TK	Trunk
TN	True Negative
TP	True Positive
VC	View Conversion
VD	Video Descriptor
VRNN	Vanilla RNNs

## LIST OF SYMBOLS

$\overline{(\cdot)}$	Rounding operator
$(x_c^i, y_c^i, t_c^i)$	Point coordinates in the $i^{th}$ 3D convolutional feature maps
$(x_v, y_v, t_v)$	Body joint coordinates from the original video sequence
$(r_x^i, r_y^i, r_t^i)$	Size ratio of the $i^{th}$ 3D convolutional feature maps
$(l_v, m_v, n_v)$	Trajectory point coordinates in the original video sequence
$(s_i^x)$	$X$ –axis components of stride
$(k_i^x)$	Kernel size
$N$	Total number of body joints
$O$	Total number of trajectory points in each frame
$L$	Total duration of the video series
$k$	Total number of frames in the videos
$l$	Length
$h$	Height
$w$	Weight
$\mathcal{P}$	$M \times C$ matrix
$\mathcal{B}^T$	Transposition of $\mathcal{B}$
$\mathcal{W}$	Matrix of parameters
$e$	Gradient of the loss function
$\frac{\partial e}{\partial \mathcal{A}}$	Back-propagation
$w$	Weight of the training sequences $x_i$
$C > 0$	Penalty parameter
$\ \cdot\ _1$	$l_1$ -norm
$F$	Original feature vector

$F_a$	Aggregated feature vector
$d$	Distance between the original and aggregated features
$\sigma$	Parameter that constrains the propagation scope
$Kernel(d)$	Guidance linked to the distance of $d$ based on the kernel
$N$	Normal density with a predicted value of $Kernel(d)$
$\sigma'$	Standard variance
$G(i, d)$	Guidance related to the distance of $d$ in the $i^{th}$ position
$c_j$	Distance count vector
$A_j$	Aggregated guidance vector for the feature located at location $j$
$c_j(d)$	Number of body joint and trajectory point features
$F$	Body joint location or a trajectory point feature in $F$
$pos(f)$	Collection of $f$ 's occurrence positions across clips
$[\cdot]$	Indicator function that equals 1 if the criteria is met and 0 otherwise
$l$	Length of the video sequence
$h_j$	Hidden vector at position $j$ based on BRNN
$A_j$	Aggregated position-aware guidance vector
$\tanh$	Hyperbolic tangent function
$v$	Global vector
$v^T$	Transpose vector
$d$	Difference between the actual and averaged feature vectors
$\sigma$	Variable that controls the range of the propagation
$G$	Guidance base matrix
$c_j$	Distance count vector
$A_j$	Aggregated guidance vector for the feature at position $j$

$f$	Body joint location or a trajectory point feature in $F$
$pos(f)$	Set of $f$ 's occurrence positions throughout all clips
$[\cdot]$	Indication function
$(\alpha_j)$	Attentive weight
$F_a$	Final aggregated feature vector for the entire human skeleton
$h_j$	Hidden vector at position $j$
$A_j$	Aggregated position-aware guidance vector generated
$e(\cdot)$	Score function
$\tilde{e}_k$	Transformed vector of $e_k$
$\tilde{Y}$	Tensor of edges after conversion
$\times$	3D cross product
$Co(R)$	Cofactor matrix of $R$
$T$	Transpose of the inverse $R$
$\tilde{Z}$	Tensor of surface standard vectors after conversion
$\alpha, \beta, \gamma$	$x, y, z$ rotation angles
$K$	Kernel patch
$m$	Name for this element
$\otimes$	Matrix multiplication
$p(\cdot; \pi)$	pdf with a specific $\pi$
$r_1$	Threshold chosen at random between 0 and 1
$\alpha_n^i$	New instance
$\mu$	Mean
$\Sigma$	Covariance
$\epsilon \mathcal{I}$	Noise term