# Fine-Grained Sports, Yoga, and Dance Postures Recognition: A Benchmark Analysis

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Abstract—Human body-pose estimation is a complex problem in computer vision. Recent research interests have been widened specifically on the Sports, Yoga, and Dance (SYD) postures for maintaining health conditions. The SYD pose categories are regarded as a fine-grained image classification task due to the complex movement of body parts. Deep Convolutional Neural Networks (CNNs) have attained significantly improved performance in solving various human body-pose estimation problems. Though decent progress has been achieved in yoga postures recognition using deep learning techniques, fine-grained sports, and dance recognition necessitates ample research attention. However, no benchmark public image dataset with sufficient inter-class and intra-class variations is available yet to address sports and dance postures classification. To solve this limitation, we have proposed two image datasets, one for 102 sport categories and another for 12 dance styles. Two public datasets, Yoga-82 which contains 82 classes and Yoga-107 represents 107 classes are collected for yoga postures. These four SYD datasets are experimented with the proposed deep model, SYD-Net, which integrates a patch-based attention (PbA) mechanism on top of standard backbone CNNs. The PbA module leverages the self-attention mechanism that learns contextual information from a set of uniform and multi-scale patches and emphasizes discriminative features to understand the semantic correlation among patches. Moreover, random erasing data augmentation is applied to improve performance. The proposed SYD-Net has achieved stateof-the-art accuracy on Yoga-82 using five base CNNs. SYD-Net's accuracy on other datasets is remarkable, implying its efficiency. Our Sports-102 and Dance-12 datasets are publicly available at https://sites.google.com/view/syd-net/home.

Index Terms—Sports, Dance, Yoga, Attention, Convolutional Neural Networks (CNNs), Posture Recognition, Random Erasing.

#### I. INTRODUCTION

H UMAN body-pose recognition is a challenging problem in computer vision. It is widely used in various applications, such as sports [1]–[6], yoga [7]–[14], dance [15]– [19], daily activity [20], and others [14], [21], [22]. Among these actions and postures, **S**ports, **Y**oga, and **D**ance (SYD)

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are intrinsically very important physical activities to balance functionalities of various body parts, well-being, etc. The SYD activities (Fig. 1) are crucial to improve our quality of life (QoL) and mitigating several diseases and mental health conditions, e.g., Parkinson's disease, anxiety, sleeping disorder, etc. [23]. Fine-grained image classification (FGIC) using SYD postures is difficult due to huge intra-class variations and small inter-class differences among the sub-categories. SYD express our emotion, complex body movements, gestures, costumes, and diversity. Dance is a perceptual domain integrating audio (music) and video (posture) in a synchronized manner to represent the underlying knowledge of a dance style [24]. In this direction, Indian Classical Dance (ICD) and Yoga poses (aka *asana*) effectively represent their heritage and culture since ancient times [25], [26]. Also, hundreds of dancing themes (e.g., tribal, folk, etc.) are popular across the world. These diversities are promoted in the Intangible Cultural Heritage of UNESCO, such as the Lazgi (Khorazm region in Uzbekistan) [27], Thai (Thailand) Kolo (Serbia), Lad's (Romania), Bharatnatyam (India), and others.



Fig. 1. Symbolic examples of fine-grained Sports, Yoga, and Dance (SYD) postures, represent complex body part movements and gestures, which are key challenges in posture recognition.

To address the challenges in SYD recognition, existing methods have emphasized hand-crafted features (e.g., bag-ofwords, haar wavelets, scale-invariant feature transform (SIFT), space-time interest points (STIP), moments, etc.) [28], [29], pose estimation from skeletal joints [22], [30], motion analysis using optical flow information [26], and deep convolutional features [18], [21], [31], shown in Table I. The pose estimation performance is remarkably improved using deep learning and related fusion-based techniques. Most of these methods are experimented with laboratory-simulated dance videos collected from YouTube, or other web resources, summarized in Table I. The Leeds Sports Pose (LSP) dataset [32] represents 8 sports classes. The Yoga-82 [8] comprised of 82 fine-grained yoga poses. Another dataset containing 107 yoga classes, Yoga-107, is also experimented. However, no image-based dataset with diverse variations of dance styles is publicly available. Our main motivation is to create new image-based dance and sports action datasets. We have presented the Sports image dataset with 102 actions, and the Dance image dataset with

Ref, year	Method	Input data	Dataset name and pose/actions
[32], 2010	appearance and pose-based pictorial structure model.	1000 training and 1000 testing images	Sports 8: Soccer, Tennis, etc.
[37], 2011	global scene model with a figure-centric visual word	150 clips (mean 6.39s) at 10fps	UCF Sports: kicking, lifting, rid-
	representation		ing horse, running, etc.
[38], 2014	multiple schemes to learn spatio temporal features	1 million YouTube videos, avg 5.36 min clip.	487 classes: cricket, racing, etc.
[39], 2019	spatio-temporal color-coded image called, joint an-	16,800 3D yoga videos with 400 videos per	Yoga 42: standing postures,
	gular displacement map (JADM).	pose, collected using a mocap setup.	katichakrasana, etc.
[8], 2020	classification using CNNs in a hierarchical structure	28,478 yoga-pose images are collected from	Yoga 82: Handstand, Plank, Side
		various search engines.	reclining, Shoulderstand, etc.
[7], 2022	contrastive skeleton feature representations and ex-	contains 1931 images collected from Kaggle	Yoga 45: balancing, sitting, up-
	tracts 33 keypoints using Mediapipe		ward bow pose, etc.
[40], 2013	space-time interest point descriptors computed from	330 video clips of 87 dancers at 30 fps, and	ICD - 6 styles: Bharatanatyam,
	each frame and classified by a non-linear SVM.	collected from stage performance.	Kathak, Odissi, etc.
[41], 2017	mid-level action representation using dancelets for	420 videos collected from YouTube and	HIT Dances 6 styles: Ballet, Hip-
	dance-based video recommendation.	Youku websites.	hop and 4 Chinese folks.
[42], 2018	integrates optical flow and motion data. Fusion-based	1000 videos of 10 sec. at 30 fps, a total of	Let's Dance 10 classes: Ballet,
	multi-stream 3D temporal CNNs were tested.	300000 frames.	Foxtrot, Latin, Tango, etc.
[43], 2021	Estimates 2D pose sequences, and tracks dancers.	1143 video clips of 9 genres, 154 movement	University of Illinois Dance - 9
	Simultaneously estimates corresponding 3D poses.	types of 16 body parts.	types: Ballet, Tango, etc.
[44], 2022	understanding dance semantics by spatio temporal	300 HD dance videos, collected from 6 per-	7 types: firing arrows, dance of
	dynamics using keypoints (OpenPose) and GRU.	formers in indoor and outdoor, and YouTube.	peacock, playing flute, etc.
Ours, 2023	Multi-scale patch-based attention mechanism	5967 image samples collected from Kaggle	Yoga 107: tulasana, lolasana, etc.

TABLE I

SUMMARY OF A FEW EXISTING SPORTS, YOGA, AND DANCE RECOGNITION IMAGE/VIDEO DATASETS WITH RELATED DESCRIPTIONS.

12 categories, which are the first of their kind. A new deep model is devised to simulate experimental analysis on four SYD datasets in a weakly supervised manner.

We have proposed a patch-based attention (PbA) module, namely SYD-Net (Fig. 2), that integrates spatial attention and channel attention on top of standard backbone convolutional neural networks (CNNs). Our aim is to establish a semantic correlation among a set of uniform and multi-scale patches by focusing on the most relevant image regions for defining a comprehensive feature descriptor. SYD-Net is inspired by the self-attention mechanism [33], [34], which is an integral ingredient of numerous deep architectures in computer vision and natural language processing ubiquitously. Gaussian dropout [35] is adapted to hinder overfitting. Random region erasing [36] data augmentation (Fig. 3) produces on-the-fly data diversity for effective training of SYD-Net. The major contributions of this work are:

- A patch-based attention mechanism that summarizes the discriminativeness of partial feature descriptors for fine-grained sports, yoga, and dance postures recognition.
- A new image dataset with 102 sport actions and another dataset representing 12 dance styles are proposed for posture classification avoiding part-based/skeletaljoint/bounding-box information.
- Extensive experiments are conducted using five backbone CNN architectures on four SYD datasets in a weakly supervised manner.
- The proposed SYD-Net approach achieves state-of-the-art accuracy on the Yoga-82 and Yoga-107 datasets.

The rest of this paper is organized as follows: Section II summarizes related works on SYD poses. Section III describes the proposed method. Section IV describes the datasets briefly. Section V demonstrates the experimental results of the ablation study. The conclusion is presented in Section VI.

### **II. RELATED WORKS**

Posture recognition methods can be generalized into two broader streams: a) hand-crafted, and b) deep-learning methods including, attention-based works. Some SYD pose recognition methods are summarized in Table I, and described next.

### A. Study on Sports Actions

Sports activities are primarily recognized using deep architectures. Various sports technologies and related datasets are studied and analyzed the role of computer vision technologies in sports (e.g., player and ball tracking) in [5]. The pictorial structure model (PSM) with clusters of partial pose descriptors from sports images is presented [45]. The dataset is more challenging than its earlier version, called Leeds Sports Pose (LSP) dataset [32]. The collective sports video dataset represents a multi-task recognition of both 5 collective activities and 11 sports categories [6]. Deep learning methods using CNNs and long short-term memory (LSTM) are tested for benchmark analysis. A two-stream attention model using LSTM is described for action recognition [4]. Freestyle wrestling actions are recognized from videos using a histogram of graph nodes [46]. A multi-labels DeepSport dataset is presented for automated sport understanding using videos captured at multiple views of a basketball game [1]. A CNN combining global regression and local information refinement modules for sports-pose estimation using 2D images is presented [3]. Swimming motion analysis is presented [14]. Figure Skating Dataset with 10 sports actions (FSD-10) is introduced for finegrained content analysis using a key-frame-based temporal segment network [47]. Most of the existing works on sports analysis are based on video datasets.

# B. Study on Yoga Postures

Mainly, three types of intelligent approaches for yoga pose analysis have been developed: (a) wearable device, (b) Kinect, and (c) computer vision. A hybrid multi-modal and body multi-positional system for recognizing 21 complex



Fig. 2. Proposed SYD-Net Model comprises three key modules. a) Extraction of hybrid patches, consisting of same-size uniform patches and hierarchical multi-scale regions. b) Patch-based attention module, consisting of the self-attention feature maps and further refined with the weighted-attention to define channel-attention. It is modulated with a spatial attention module to define an attentional feature map. c) Finally, the compact feature vector is regularized with the Gaussian dropout and batch normalization prior to the softmax layer for classification.

human activities using wearable devices is developed [48]. The CNNs recognize yoga poses from 3D motion capture data by integrating a joint angular displacement map (JADM) comprising 39 joints of yoga action skeletons [39]. A yoga pose grading approach is described using contrastive skeleton feature representations [7]. Many approaches have used OpenPose to estimate the keypoints/joints in developing Yoga pose recognition and mobile applications for self-assessment and yoga assistance [49]-[51]. A yoga self-coaching system using an interactive display in real time is developed to avoid incorrect postures [52]. It classifies 14 yoga postures based on transfer learning. The fitness actions of 28 poses are classified into three categories of exercises [10]. Likewise, 88 videos are used for classifying 6 Yoga poses [49]. Yoga-82 [8] has introduced a new dataset containing almost 28.5k images of 82 fine-grained yoga poses, and illustrated in Fig. 7. This dataset is tested in our study for further improvement.

### C. Study on Dance Postures

Traditional hand-crafted feature-based and deep learning approaches are developed for dance posture recognition. The bag-of-words method is applied to recognize five Greek dance styles from videos [53]. The space-time interest point (STIP) detection and their description from videos using a 3D facet model are presented [54]. A spatio temporal Laban feature descriptor (STLF) from YouTube videos is described [55]. Using a Kinect sensor, 3D skeletal information of 25 leg postures from five dancers representing Odissi dance has been collected, and a similarity function is used for recognition [30]. Multiple kernel learning using a directed acyclic graph is presented [29]. With music, *Kathakali* demonstrates complex hand gestures, body movements, and facial expressions. The dataset contains 654 images representing 24 mudras of Kathakali and was tested using CNN [56]. Bharatanatyam posture recognition is tested on audio and video data using the Gaussian mixture model (GMM), support vector machine (SVM), and CNN [57]. Dance semantics understanding from videos by deep pose estimation (based on OpenPose) coupled with a gated recurrent unit (GRU) is presented [44]. The

Inception-v3 features, 3D CNN features, and pose signature based on AlphaPose estimation are combined and fed into an LSTM for building spatio temporal relationships for ICD classification [58]. A model based on ResNet-50 recognized eight ICD [59]. An Uzbek national dance, *Lazgi* classification and recognition using an optical motion capture system are explored [27]. According to our study, image datasets representing various sport actions and dance styles are unavailable for weakly supervised pose estimation. This work presents two new image datasets for sport and dance actions recognition.

### **III. PROPOSED METHOD**

Sports, Yoga, and Dance (SYD) involves complex movements of body parts and subtle variations in expression and gesture, e.g., yoga and dance poses. Human-object interactions could also be involved, e.g., players with a football in sports. Various pose-estimators, object detectors, skeletal joints, and body parts are often used to solve the problem. The recognition task becomes more challenging when multiple persons are involved in an activity. In some cases, extraction and localization of body keypoints of multiple persons from a still image could be burdensome, and difficult to formulate an appearance-based model. Sometimes, a global descriptor overlooks finer details, which are essential for FGIC [60]. Our intuitive approach is that region-based partial feature description could be an alternative solution in capturing finer details of SYD poses for classification. Our target is to devise an end-to-end trainable deep architecture to classify these complex fine-grained human postures avoiding any bounding-box annotation, object/pose detector, and body keypoints/joints, commonly used in existing works. Moreover, the random erasing technique with conventional data augmentation is followed for additional benefits to ease overfitting and overall performance gain. The proposed SYD-Net, conceptualized in Fig. 2, is divided into three parts: a) computing a set of non-overlapped patches with fixedsize and multi-scale region proposals, b) patch-based attention module, and c) classification. Functionalities of all modules are described next.



(a) Fixed RGB=127

(b) Random RGB

Fig. 3. Patches with random erasing image augmentation. (a) Erased full image with fixed RGB=127;  $4 \times 4$  uniform, and multi-scale patches, enclosed by rectangles. (b) Two random regions erased with random RGB colors on both types of patches.

#### A. Uniform and Multi-Scale Patch Proposals

In an image, contextual information and associated object(s) provide a vital cue to understand human activity, evident in various sports (Fig. 5). Here, a patch-based approach is devised to learn overall semantics and contexts from various image parts at multiple scales (Fig. 3). We aim to integrate detailed information from several smaller non-overlapping image patches into a comprehensive feature descriptor. Moreover, hierarchical regions establish a semantic correlation and contextual representation among the feature maps. The uniform patches focus on finer details in each small region. Whereas larger multi-scale patches summarize overall feature representation holistically. Thus, combining these two key aspects through an attention mechanism improves overall efficiency for subtle discrimination in fine-grained SYD postures.

Let a color input image  $I_l \in \mathbb{R}^{h imes w imes 3}$  is fed into a backbone CNN, such as MobileNet-v2 with class-label l. A backbone network  $\mathcal{N}$  extracts high-level feature maps **F**  $\in \mathbb{R}^{h imes w imes c}$  where h, w, and c denote the height, width, and channels, respectively. The input image  $I_l$  is divided into a set (D) of non-overlapping uniform patch proposals. The resulting number of small regions is  $e = (h \times w)/a^2$ , where  $a \times a$  is the spatial size of a rectangular patch d. Set  $D = \{d_1, d_2, ..., d_e | I_l\}$  consists of e parts. A small patch  $d_i$  is defined with its spatial dimension  $p_i = [x_i, y_i, \Delta w, \Delta h]$ , and here  $\Delta w = \Delta h = a$  is uniformly the same for all patches. Each patch is denoted as  $d_i = [\mathbf{F}_i, p_i]$ , where  $\mathbf{F}_i$  is the feature map of patch  $p_i$ . In addition, multi-scale patches are defined to capture complementary information hierarchically, where the patch sizes are progressively increasing. It can be defined as  $p_i = [x_i, y_i, \Delta w_i, \Delta h_i]$  and  $p_j = [x_j, y_j, \Delta w_j, \Delta h_j]$  such that  $\Delta w_i > \Delta w_j$  and  $\Delta h_i > \Delta h_j$ , where  $p_i > p_j$  regarding the spatial dimension of  $p_i$  and  $p_j$  patches, respectively. Finally, a collection of all n patches (*i.e.*, uniform and multiscale) is denoted as  $P = \{p_i\}_{i=1}^{i=n}$ , and corresponding feature map is  $\mathbf{F} = \{\mathbf{F}_i\}_{i=1}^{i=n} \in \mathbb{R}^{n \times (h \times w \times c)}$ . The feature map of each patch is  $\mathbf{F} = \{\mathbf{F}_i\}_{i=1}^{i=n} \in \mathbb{R}^{n \times (h \times w \times c)}$ . each patch is determined through a mapping between the correspondence of smaller regions within the actual highlevel output feature maps, extracted using a base network  $\mathcal{N}$ . Firstly, **F** is upsampled to a higher resolution  $k(h \times w)$  for this intent. Then, bilinear interpolation is applied for pooling features from every patch. The upsampling is regarded as a mapping  $m: \mathbf{F} \to \mathbf{F} \in \mathbb{R}^{k(h \times w) \times c}$ , where actual spatial size  $(h \times w)$  is scaled up by k times before pooling. Though P represents patches of various sizes, bilinear pooling renders the feature vectors of the same sizes for all patches, which are kept the same as the output dimension of base CNNs, i.e.,  $\mathbf{F} \in \mathbb{R}^{(h \times w \times c)}$ , and denoted as  $\mathbf{F}$ .

# B. Patch-based Attention (PbA) mechanism

Attentional feature description is proliferated ubiquitously in image recognition and others to improve performance. Here, attention is performed in two paths, patch-based channel attention and spatial attention, which are finally integrated together. It fuses both to summarize essential features by exploring where to focus and what to emphasize simultaneously in the feature maps F. Self-attention acts across the channel-based feature maps of all patches to capture channelwise relationships. It relates inter-channel feature interactions among patches and estimates their relevance correspondingly. Cross-channel attention investigates the importance of feature maps (what) to enhance learning capability. On the contrary, spatial attention explores neighborhood structural interpretation for producing a spatial attentional mask (where) for further refinement of aggregated feature summarization. These dualattention pathways empower significantly and act complementarily to render a global information for distinguishing subtle variations in SYD recognition.

1) Channel Attention (CA): Channel attention is adapted from self-attention mechanism that tackles long-range dependency by generating a context vector based on the weighted sum of feature space [33], [34]. In self-attention, the query  $\mathbf{Q}$ , key  $\mathbf{K}$ , and value  $\mathbf{V}$  are learned from the same input feature vector  $\mathbf{F}$ . The attention-weight matrix is a dot product of  $\mathbf{Q}$  and  $\mathbf{K}$ , multiplied by  $\mathbf{V}$  to generate an attention-focused feature map. We have applied [Q, K, V] attention principle for a patch  $p_i$  and its neighbors  $p_j$  patches ( $i \neq j$ ). We aim to generate an attentional feature descriptor, *i.e.*, value  $\mathbf{V}$  that focuses on the relevant and discriminative regions.  $\mathbf{F}_i$  and  $\mathbf{F}_j$  are high-level feature vectors computed from  $p_i$  and  $p_j$  patches, respectively. The attentional feature map is given as

$$\psi_{i,j} = tanh(\mathbf{W}_{\psi}\mathbf{F}_{i} + \mathbf{W}_{\psi'}\mathbf{F}_{j} + \mathbf{b}_{\psi}),$$
  
$$\vartheta_{i,j} = \sigma\left(\mathbf{W}_{\vartheta}\psi_{i,j} + \mathbf{b}_{\vartheta}\right)$$
(1)

where  $\mathbf{W}_{\psi}$  and  $\mathbf{W}_{\psi'}$  are the weight matrices to compute attention vectors using  $p_i$  and  $p_j$  patches, respectively;  $\mathbf{W}_{\vartheta}$  is their nonlinear combination;  $\mathbf{b}_{\psi}$  and  $\mathbf{b}_{\vartheta}$  are the bias vectors, and  $\sigma(.)$  is element-wise nonlinear activation. The next objective is to compute the importance of each  $p_i$  through a weighted sum of attention scores of all patches, given as

$$\delta_{i,j} = softmax(\mathbf{W}_{\delta}\vartheta_{i,j} + \mathbf{b}_{\delta}), \ \hat{\mathbf{F}}_{i} = \sum_{j=1}^{n} \delta_{i,j}\mathbf{F}_{j}$$
(2)

where  $\mathbf{W}_{\delta}$  is the weight matrix, and  $b_{\delta}$  is the bias vector. The aggregated feature space is  $\hat{\mathbf{F}}_i$  which is summarized through a global average pooling (GAP) layer to generate  $\tilde{\mathbf{F}}_i$  for all patches in *P*. The result  $\tilde{\mathbf{F}}_i$  is passed through a *softmax* layer for producing a weighted attention matrix  $\phi_i$ . Finally, their

weighted sum  $\mathbf{F}_{CA}$  is considered as the output of the crosschannel attention (CA) mechanism, and is given as

$$\tilde{\mathbf{F}}_{i} = \mathcal{GAP}\left(\hat{\mathbf{F}}_{i}\right), \ \mathbf{F}_{CA} = \sum_{i=1}^{n} \phi_{i} \tilde{\mathbf{F}}_{i}$$
where,  $\phi_{i} = softmax(\mathbf{W}_{\phi} \tilde{\mathbf{F}}_{i} + \mathbf{b}_{\phi})$ 
(3)

2) Spatial Attention (SA): Spatial attention captures the neighborhood information to calibrate feature representation by generating an attentional mask for refining the global structural information. This mask builds spatial relationships by correlating *where to pay attention* in the feature space. Thus, it effectively localizes the most informative region(s) for global semantic representation of SYD postures.

No parameter optimization is required in the global average pooling (GAP), and it helps to avoid overfitting [61]. GAP sums out spatial information; thus, it is more robust to spatial translations of input. It can play as a structural regularizer in the network. Here, GAP is applied to refine spatial features **F** from all patches *P*. It downsamples the channel dimension precisely to  $(h \times w \times 1)$  by summarizing the mean features and generatig  $\mathbf{F}_{gap}$ . Compared to GAP (.), global max pooling (GMP) emphasizes the most important features from crosschannels and generates an optimized feature vector  $\mathbf{F}_{gmp}$ . A combination of both pooling improves learning efficiency compared to any single pooling [62]. The fused feature map  $\mathbf{H} \in \mathbb{R}^{n(h \times w \times 2)}$  is defined as

$$\mathbf{H} = concat \left( \mathcal{GAP} \left( \mathbf{F} \right); \mathcal{GMP} \left( \mathbf{F} \right) \right)$$
(4)

where, the feature pooling is  $\mathbf{F} \to \mathbf{F}_{gap}$  :  $\mathbb{R}^{n(h \times w \times 1)}$ , and same for  $\mathbf{F}_{gmp}$ . Next, a multi-layer perceptron (MLP) is applied to generate a spatial attention mask  $\mathbf{F}_{SA}$ . A MLP layer comprises a flatten, softmax, Gaussian dropout, and batch normalization layers. We aim to compute weighting factors based on the probabilities rendered by softmax activation. The probabilities are computed by a dense layer with the same size as base CNNs output channels  $1 \times c$ .

$$\mathbf{F}_{SA} = \mathcal{MLP}(\mathbf{H}); (softmax + \lambda_{GD+BN}) \Rightarrow \mathcal{MLP} \quad (5)$$

where  $\lambda_{GD+BN}$  denotes a regularization ( $\lambda$ ) process with a Gaussian dropout (GD) and batch normalization (BN) layers. The spatial attention mask is  $\mathbf{F}_{SA} \in \mathbb{R}^{(1 \times c)}$ . This patch-level spatial attention ( $\mathbf{F}_{SA}$ ) mask is multiplied element-wise with the weighted attention vector  $\mathbf{F}_{CA}$ , rendered from channel attention method. It modulates overall feature representation and empowers discriminability by capturing subtle details with focusing on global structural information, as essential for FGIC. A residual path is connected with  $\mathbf{F}_{CA}$  for smoother gradient flow in learning. Finally, a patch-based attention (PbA) feature vector  $\mathbf{F}_{PbA} \in \mathbb{R}^{(1 \times c)}$  is obtained.

$$\mathbf{F}_{PbA} = \left(\mathbf{F}_{CA} \otimes \mathbf{F}_{SA} + \mathbf{F}_{CA}\right) \tag{6}$$

3) Classification: The upsampled feature **F** is squeezed by a GAP layer to produce a vector of  $(1 \times c)$  channels which is added with attentional feature map **F**<sub>PbA</sub>. The final feature



Fig. 4. Baseline approach using attention over CNN's output features.

vector  $\mathbf{F}_{f}$  is regularized and passed to a softmax layer to compute an output vector implying the class probabilities.

$$\mathbf{F}_{f} = \mathbf{F}_{PbA} + \mathcal{GAP}\left(\mathbf{F}\right) \; ; \; Y_{pred} = softmax(\lambda(\mathbf{F}_{f})) \quad (7)$$

Gaussian dropout (GD) [35] and batch normalization (BN) regularizers are applied to avoid overfitting issues and denoted as  $\lambda$ . The GD can generalize learning tasks effectively than a simple dropout layer. Typically, GD uses multiplicative noise, and the dropout rate  $\phi$  maps to the noise standard deviation  $\sigma_{noise}$ . This hyperparameter is computed as  $\sigma_{noise}(\rho) = \sqrt{\rho \cdot (1-\rho)^{-1}}$ . The noise distribution is free of learnable parameter. The categorical cross-entropy loss function  $\mathcal{L}_{ce}(Y_{true}, Y_{pred})$  minimizes the error rates between the actual class-label  $(Y_{true})$  and predicted class-label  $(Y_{pred})$  during the learning task. The proposed SYD-Net is end-to-end trainable and the attention module could be added with standard backbones to enhance efficiency.

#### C. Attention-based Baseline Method

In addition to the conventional baseline evaluation, the attention mechanism is applied to compute baseline results (Table III). We aim to observe the suitability of hybrid patches in improving the accuracy of attention-based baseline results using different backbone CNNs. A pictorial representation of the attention-based baseline is shown in Fig. 4. In this method, firstly, the high-level feature map from a backbone CNN is extracted. Subsequently, the self-attention and weighted attention techniques are exploited for re-weighting the base CNN's output features. Lastly, a softmax layer is applied to the attentional feature description for classification.

In summary, three methods are explored for baseline assessment: (a) simple classification method using high-level feature vector of a base CNN with conventional data augmentation; (b) similar classification strategy as (a), with additional random erasing data augmentation for more data-diversity; and (c) leveraging attentional weights over base CNN's features in conjunction with (b), shown in Fig. 4. Description of baseline evaluations is given in Sec. V-B. Indeed, our attention-based baseline performance outperforms the traditional baseline method that only uses base CNN's output features.

#### **IV. DATASET DESCRIPTION**

We have described the Sports-102, Yoga-82, Yoga-107, and Dance-12 datasets which provide only class labels, avoiding bounding-box annotations, and summarized in Table II.

1) Sports-102 Dataset: The sports dataset represents 102 sports-action classes representing complex human body postures. Sports-102 comprises various games, some of which are based on individual performers (*e.g.*, golf, javelin, etc.) while others are team-based (*e.g.*, hockey, kabaddi, etc.) with diversity. Samples of various sports are shown in Fig. 5. The



Fig. 5. Examples of diverse sport actions from the Sports-102 dataset.



Fig. 6. Class-wise train-test image distribution of Sports-102 dataset. Best view of the class labels in zoom.



(a) Yoga-82 dataset

Fig. 7. Examples of various asanas from the Yoga-82 [8] and Yoga-107 datasets.

training and testing data distribution of various sports categories are shown in Fig. 6. Mainly, the images are collected from Kaggle<sup>1</sup> repository, and related websites. Though few video-based datasets exist for dance and sport actions, no such image-based datasets are publicly available for research, to the best of our knowledge.

2) Yoga-82 [8] and Yoga-107 Datasets: These are publicly available datasets. Samples of various postures of Yoga-82 are illustrated in Fig. 7.a. After careful observation, a few samples are rejected, which are irrelevant. The reason might be the resolution, format, size, other characteristics of images, and repetition of the same images. Some poses (asana) representing the cartoon's and animal's images are irrelevant to the current problem, so, eliminated. Thus, samples from various yoga classes are discarded to formulate a well-defined and precise Yoga-82 sub-dataset. Actual Yoga-82 contains 21.0k training and 7.4k testing samples. Whereas we have tested on 19.9k training and 7.2k testing images after standardization.

The Yoga-107 dataset is collected from Kaggle<sup>2</sup> repository and a few samples are shown in Fig. 7.b. It contains 107 fine-grained classes of yoga poses, comprising a total of 5.9k images. It is a challenging yoga dataset as the classes are more than 100, and the asana samples per class are much lesser than Yoga-82.

3) Dance-12 Dataset: A total of 12 dance styles are incorporated in the Dance-12 dataset representing diverse variations in postures, number of persons, background, theme, and other factors. This dataset represents the following

TABLE II DATASET SUMMARY AND TOP-1 ACCURACY (%) OF SYD-NET TRAINED FROM SCRATCH AND WITH IMAGENET WEIGHTS USING XCEPTION.

Dataset	Train	Test	Class	Xcep (srth)	Xcep (ImNet)
Sports-102	9278	4315	102	96.70	98.86
Yoga-82	19941	7241	82	97.29	97.80
Yoga-107	4084	1883	107	82.00	85.20
Dance-12	3129	1694	12	92.24	97.98

dance categories: Ballet, Hip-hop, Pole, Salsa, Samba, Bharatnatyam, Chaau, Dandya, Dhunuchi, Kathak, Kalbelia, and Manipuri. The first five dances are internationally popular and the remaining seven are Indian. All the images are collected freely from various public websites such as Google, Yahoo, Bing, etc. Samples of international and Indian dance genres are illustrated in Fig. 8. The training and testing splits of various dance styles are given in Fig. 9. The purpose of our data collection is research only. No commercial gain or unethical issue is involved in our research. Dance-12 is growing a dataset in size and variations. We will include several more classical and folk dance styles from various countries around the world in the near future. This dataset is publicly available at https://sites.google.com/view/syd-net/home.

## V. EXPERIMENTAL RESULTS

Firstly, we have analyzed the experimental details of SYD-Net. Next, an ablation study is presented to evaluate the significance of key components of the SYD-Net model.

## A. Implementation

Our model is implemented using ResNet-50 [63], DenseNet-201 [64], NASNetMobile [65], MobileNet-v2 [66], and Xcep-

<sup>&</sup>lt;sup>1</sup>www.kaggle.com/datasets/gpiosenka/sports-classification

<sup>&</sup>lt;sup>2</sup>https://www.kaggle.com/datasets/shrutisaxena/yoga-pose-imageclassification-dataset



(c) Salsa Fig. 8. Examples of various dance styles from the Dance-12 dataset.



Fig. 9. Training-testing image distribution of Dance-12 dataset.

tion [67] backbone CNNs in TensorFlow-2.x with cuDNN 7.6. The input image resolution is  $224 \times 224$ , and the output feature map of the MobileNet-v2 backbone is 7×7×1280. Whereas, the output feature maps of other backbones represent the same spatial size, but differ in channel dimensions. The patch sets are extracted along the spatial dimension [68]. The spatial size of base output  $(7 \times 7)$  is upsampled to  $48 \times 48$ for extracting the patch sets from  $P_9$  to  $P_{20}$ . The upscaled resolution is 45×45 for proper pixel alignment with the patchsizes of  $P_{25}$  and  $P_{30}$ . Three sets of uniform patches (3×3,  $4 \times 4$ , and  $5 \times 5$ ) and corresponding hierarchical regions are generated. For example, with 16 uniform patches, 4 multiscale patches are computed in a hierarchical manner from the center of the input image with the smallest  $12 \times 12$  size, and incremented to  $24 \times 24$ ,  $36 \times 36$ , and finally to  $48 \times 48$ size. Altogether 16 uniform and 4 hierarchical patches are considered in set  $P_{20}$ . Likewise,  $P_{12}$  and  $P_{30}$  are generated. Initially, the input image size is 256×256. We have applied standard data augmentations of random rotation ( $\pm 25$  degrees) and random scaling (1±0.25). Two randomly selected regions of total size or a single region with size (0.1-0.8) are erased with either a fixed RGB=127 or random RGB pixel-values at a time (Fig. 3), and applied on-the-fly for image augmentation. Then, random cropping is applied to select an image size of 224×224 as input to CNNs. SYD-Net is trained from scratch for initializing base CNNs for a fair comparison, as well as trained with ImageNet weights in separate experiments. The Stochastic Gradient Descent (SGD) is used to optimize the categorical cross-entropy loss function with an initial learning rate of 0.007 and multiplied by 0.1 after every 50 epochs. The model is trained for 200 epochs with a mini-batch size of 8 using a Tesla M10 GPU of 8 GB. A Gaussian dropout rate 0.2 and batch normalization are applied to avoid overfitting. The top-1 and top-5 accuracy (%) metrics are used for performance evaluation, and the model's parametric complexity is estimated in millions (M).

(e) Bharatnatyam

(f) Manipuri

(g) Chhau

(h) Kalbelia

# TABLE III

TOP-1 BASELINE ACCURACY (%) USING CONVENTIONAL DATA AUGMENT (TOP ROW-SET), RANDOM ERASING AUGMENT (MID ROW-SET), AND ATTENTION WITH RANDOM ERASING (LAST ROW-SET). THE LAST COLUMN SHOWS MODEL PARAMETERS IN MILLIONS (M).

Base CNNs	Sports	Yoga-82	Yoga-107	Dance	Par (M)
ResNet-50	68.34	75.52	52.13	63.44	23.8
DenseNet-201	74.21	80.16	55.12	68.12	18.5
MobileNet-v2	75.70	79.73	60.31	63.80	2.4
Xception	79.10	81.93	62.87	72.27	21.1
ResNet-50	70.91	77.56	55.28	63.80	23.8
DenseNet-201	76.69	80.60	57.47	68.24	18.5
MobileNet-v2	77.62	82.23	65.10	65.58	2.4
Xception	80.17	83.78	66.50	72.92	21.1
ResNet-50	70.96	80.60	57.31	60.90	23.9
DenseNet-201	77.18	83.63	58.38	68.95	18.6
MobileNet-v2	77.22	83.31	65.86	68.06	2.4
Xception	82.88	85.67	67.52	73.34	21.2

### B. Performance Analysis

The performances of SYD-Net have been evaluated considering several important aspects, discussed next.

1) Baseline Results: First, baseline performances of four backbone CNNs (trained from scratch) are computed on four datasets. The results are given in Table III. Three sets of experiments are conducted for a baseline evaluation, as aforesaid. In the first set of experiments (top row set), conventional data augmentations, *i.e.*, rotation, scaling, and cropping are applied. In addition to the general augmentation, random region erasing is applied in the second set of experiments, given in the middle row set. In both experiments, we considered the output feature maps of base CNNs, and then applied global average pooling (GAP) prior to classification layer. In the last set of experiments (bottom row set), the erasing-based data augmentations remain the same.

Moreover, the attention module is applied as an alternative to GAP on base CNNs feature maps. However, the patches are not included in any baseline assessment (Fig. 4). The baseline performances have been improved using random erasing over traditional augmentation techniques. Also, attention has enhanced the baseline accuracy over GAP with a little overhead regarding the model parameters (approx +83K).

2) SYD-Net's Performance: The accuracy of SYD-Net is improved significantly by incorporating an attention module (PbA) over hybrid patches. The performances of a different number of patches using four base CNNs i.e., ResNet-50 (RN-50), DenseNet-201 (DN-201), MobileNet-v2 (MN-v2), and Xception (XN) are evaluated on all four datasets, and the results are given in Table IV. It evinces that uniform (U) patches could attain good results over baseline accuracy. Moreover, uniform patches in conjunction with hierarchical (H) regions boost the performance further by summarizing

 TABLE IV

 TOP-1 ACCURACY (%) OF SYD-NET (SCRATCH) WITH ATTENTION

 MODULES USING VARIOUS UNIFORM (U) AND HIERARCHICAL (H)

 PATCHES:  $P_9$ ,  $P_{12}$ ,  $P_{16}$ ,  $P_{20}$ ,  $P_{25}$ , and  $P_{30}$ . Two Random Erased

 REGIONS WITH BASIC IMAGE AUGMENTATIONS ARE APPLIED.

CNNs	Patch	Sports	Yoga82	Yoga107	Dance	Par(M)
RN-50	$P_9$	88.10	91.43	70.19	78.61	32.0
	$P_{12}$	89.37	92.56	70.67	79.03	32.7
	$P_{16}$	89.51	93.49	71.03	81.33	33.4
	$P_{20}$	90.23	93.77	71.90	82.52	34.2
	$P_{25}$	90.51	93.56	73.02	82.40	35.2
	$P_{30}$	91.37	93.92	75.00	84.18	36.2
DN-201	$P_9$	90.60	94.24	68.32	83.42	26.1
	$P_{12}$	91.32	94.94	69.71	83.00	26.8
	$P_{16}$	92.55	95.48	71.90	83.94	27.6
	$P_{20}$	92.85	95.75	72.32	85.24	28.3
	$P_{25}$	92.83	95.46	73.50	85.37	29.2
	$P_{30}$	93.36	95.87	74.73	88.03	30.0
MN-v2	$P_9$	93.50	94.66	75.26	84.36	7.5
	$P_{12}$	93.20	95.02	76.22	84.60	7.9
	$P_{16}$	92.90	95.06	77.67	85.42	8.4
	$P_{20}$	93.92	95.63	78.10	86.20	8.9
	$P_{25}$	93.22	94.96	78.84	86.85	9.6
	$P_{30}$	94.78	96.00	79.54	87.73	10.2
XN	$P_9$	95.66	96.35	71.36	87.50	29.3
	$P_{12}$	95.89	96.68	77.72	89.21	29.9
	$P_{16}$	95.40	96.40	79.54	90.10	30.7
	$P_{20}$	96.03	96.76	80.19	90.22	31.5
	$P_{25}$	96.21	96.50	80.76	91.40	32.5
	$P_{30}$	96.70	97.29	82.00	92.24	33.5

 TABLE V

 SYD-Net's Top-1 Accuracy(%) using NASNetMobile (Scratch)

Method	Sports	Yoga-82	Yoga-107	Dance	Param (M)
Erasing BL	70.82	77.61	56.20	66.35	4.4
$P_{20}$	90.62	94.08	72.70	83.88	9.8
$P_{30}$	91.58	94.70	74.09	84.12	12.4

contextual descriptions at multiple granularities. We have defined three sets of mixed patches:  $P_9$  contains  $3 \times 3=9$  (patchsize 16×16 pixels),  $P_{16}$  represents 4×4=16 (patch-size 12×12) pixels), and  $P_{25}$  represents 5×5=25 (patch-size: 9×9 pixels) uniform (U) regions. It is clear that more patches attain better results. For example,  $P_{25}$  renders better results than  $P_9$  and  $P_{16}$ . To enhance the accuracy of uniform patches further, 3 hierarchical regions are included with  $P_9$  to produce  $P_{12}$ (9U+3H) hybrid patches. Likewise, 4 multi-scale regions are included with  $P_{16}$  to generate  $P_{20}$  (16U+4H) patches, and 5 multi-scale regions are included with  $P_{25}$  to generate  $P_{30}$ (25U+5H) patches, respectively. The results imply that hybrid regions could improve accuracy over all three  $(P_9, P_{16}, and$  $P_{25}$ ) sets of uniform patches. Finally, set  $P_{30}$  achieves the best performance among all patch sets. MobileNet-v2 achieves competitive results compared to heavier backbones. Thus, another light-weight CNN, NASNetMobile, is tested on these datasets additionally. Only the baseline with random erasing augmentation (Erasing BL),  $P_{20}$ , and  $P_{30}$  are considered in this precise experiment. The results of NASNetMobile trained from scratch are given in Table V. Both MobileNet-v2 and NASNetMobile, albeit lightweight, have attained competitive accuracy over other base CNNs.

Next, the top-5 accuracy (%) of SYD-Net using  $P_{30}$  with two random erased regions trained from scratch are given in Table VI. All backbone CNNs attain excellent top-5 accuracy on four SYD datasets. Now, SYD-Net is trained with pre-

TOP-5 Accuracy(%) of SYD-Net with  $P_{30}$ , Trained from Scratch

CNNs	Sports-102	Yoga-82	Yoga-107	Dance-12
ResNet-50	98.89	99.42	95.67	98.22
DenseNet-201	99.40	99.20	96.20	98.93
NASNetMobile	99.07	99.60	95.99	98.69
MobileNet-v2	99.60	99.78	97.95	98.70
Xception	99.81	99.42	98.39	99.70

trained *ImageNet* weights to observe its efficiency. This experiment is conducted with both lightweight CNNs, and the best performer Xception considering random erasing augmentation. The results are given in Table VII. The accuracy is improved by a significant margin using *ImageNet* weights on  $P_{20}$  and  $P_{30}$  compared to training from scratch (Table IV). Also,  $P_{30}$ offers a little accuracy gain over  $P_{20}$ .

Furthermore, SYD-Net is tested on the Yoga-107 dataset trained with *ImageNet* weight initialization using four base CNNs, considering all combinations of patches and random erasing data augmentation, as defined above. The top-1 accuracies are provided in Table VIII. The best performance on Yoga-107 is 87.17%, achieved by DenseNet-201 with  $P_{30}$  patches. Also, other CNNs have achieved competitive results, *e.g.*, Xception achieved the second-best accuracy of 85.20%.

TABLE VII TOP-1 ACCURACY (%) OF SYD-NET TRAINED WITH IMAGENET WEIGHTS USING TWO ERASED REGIONS WITH RANDOM VALUES

CNNs	Model	Sports	Yoga-82	Yoga-107	Dance
NASNetMobile	BL	91.53	88.48	73.34	88.27
	$P_{20}$	97.56	94.44	83.92	95.80
	$P_{30}$	98.21	96.58	84.61	96.74
MobileNet-v2	BL	93.11	90.73	75.64	87.38
	$P_{20}$	98.37	97.20	83.60	96.50
	$P_{30}$	98.70	97.41	85.14	96.80
Xception	BL	94.48	91.29	73.34	88.74
	$P_{20}$	98.81	97.41	84.18	97.15
	$P_{30}$	98.86	97.80	85.20	97.98

TABLE VIII

TOP-1 ACCURACY (%) OF SYD-NET TRAINED WITH IMAGENET WEIGHTS ON YOGA-107. THE TERMINOLOGIES ARE DENOTED AS: RN50 FOR RESNET-50; DN201 FOR DENSENET-201; XN FOR XCEPTION; MNv2 FOR MOBILENET-v2; BL FOR BASELINE; AND  $P_i$  FOR PATCHES.

CNN	BL	$P_9$	$P_{12}$	$P_{16}$	$P_{20}$	$P_{25}$	$P_{30}$
RN50	74.20	80.76	81.99	82.42	83.11	83.60	85.04
DN201	77.83	83.06	85.84	86.48	86.54	86.75	87.17
MNv2	75.64	79.22	80.87	82.66	83.60	84.56	85.14
XN	74.41	82.21	83.65	83.97	84.18	84.33	85.20

3) Model Parameters: The complexity of SYD-Net in terms of model parameters: The complexity of SYD-Net in given in the last column of Table III-V. MobileNet-v2 and NASNetMobile are lightweight backbones than other CNNs, regarding the model complexity. The model parameters of  $P_9$ and  $P_{30}$  patch sets using MobileNet-v2 are 7.5M and 10.2M, respectively. Next, NASNetMobile's baseline parameters are 4.4M, and  $P_{30}$  requires 12.5M. Thus, the parametric complexity of  $P_{30}$  using NASNetMobile backbone is the second lowest (after 10.2M parameters of MobileNet-v2) among all five CNNs used here. MobileNet-v2 attains balanced performances on SYD datasets with lesser model parametric overhead, whereas SYD-Net using Xception backbone has attained the best accuracy with higher model parameters (33.5M). The accuracies of other base CNNs are satisfactory, and useful for benchmarking the SYD datasets.



Fig. 10. Performance comparison of SYD-Net with  $P_{30}$  using five different backbone CNNs trained from scratch. (a) Top-1 accuracy on Yoga-107. (b) Accuracy density on four datasets using five backbone CNNs.

#### C. Comparative Study on Efficiency of Backbone CNNs

Few works tested on small-scale datasets have witnessed that MobileNet-v2 could achieve better performance than ResNet-50. A reason could be the fundamental design aspects of these standard backbones. ResNet family exploits shortcut connections (i.e., identity mapping) to avoid performance degradation problem. This conjecture is further improved by introducing bottleneck layers where parameter-free identity shortcuts are crucial in the network at a deeper level. On the contrary, Xception is hypothesized by utilizing the inception module and separable convolutions for decoupling the spatial and channel-wise feature correlations. MobileNetv2 is built upon the depth-wise and point-wise separable convolutions and the inverted residual with linear bottleneck layers. Moreover, ReLU6 non-linearity is used for handling robustness issues at a lower dimensional feature representation. Overall, this lightweight architecture directs to a faster and memory-efficient implementation than standard convolution, which is used as a main building block of other backbones. The compact, lightweight architecture of MobileNet-v2 leads to a higher computational and accuracy gain over other backbone CNNs. A comparative study on Yoga-107 using five base CNNs is shown in Fig. 10.a, and Xception renders the best accuracy among all CNNs. The results indicate superior performances of both lightweight CNNs compared to other heavier backbones, ResNet-50, and DenseNet-201 i.e., densely connected between layers [64]. The results on Yoga-82, as reported in [8], imply that the MobileNet family outperforms the ResNet family. NASNetMobile attained competitive results *i.e.*, the differences between the accuracies of NASNetMobile and ResNet-50 on various fine-grained datasets are small in [20]. Thus, the results reported in various works evince the better capacity of lightweight MobileNet-v2 and NASNetMobile base CNNs. Herein, the efficacy of both lightweight CNNs is clear from the baselines and patched-based results.

To delve insight into the model's capacity, the performances of various base CNNs could be analyzed with the top-1 accuracy density, *i.e.*, the ratio of top-1 accuracy and the number of model parameters, as defined in [69]. A higher accuracy density value implies a higher efficiency of a deep network. It indicates how efficiently the parameters contribute to the model's capacity and expressiveness through successive layers of transformation and non-linearity. In [69], MobileNetv2 attained better accuracy density than other base CNNs, *e.g.*, ResNet-50. Our analysis of accuracy density follows a similar trend. A comparative study of accuracy density rendered by five base CNNs on four datasets is shown in Fig. 10.b. As aforesaid, a worthy reason of attaining a higher accuracy density is the powerful and precise architectural design of MobileNet-v2.



Fig. 11. Confusion matrices of SYD-Net with  $P_{30}$  on Dance-12 using MobileNet-v2, and Xception base CNNs. Best viewed in zoom.

#### D. Performance Comparison on Yoga-82 and Yoga-107

The pioneering work on Yoga-82, considering 82 classes and using a variant of DenseNet-201, has attained the best 79.35% top-1 and 93.47% top-5 accuracy, respectively. The performances on Yoga-82 using various CNNs are given in Table IX. The best performances of our approach are compared fairly using different CNNs trained from scratch. It is evident that SYD-Net outperforms those existing methods by a significant margin and achieves state-of-the-art results. The accuracies of our baseline methods are higher than actual Yoga-82. As a result, the top-1 and top-5 accuracy of SYD-Net using various CNNs are significantly higher than existing works on Yoga-82. The body key-points-based classifier ensemble method has achieved 80.14% top-1 accuracy [13]. Fusion of DenseNet-161 and KNN model achieves 79% accuracy while DenseNet-161 alone can attain 81% accuracy in Pose tutor [11]. On the contrary, SYD-Net has achieved at least a 14% gain in top-1 accuracy using various CNNs.

In Yoga-45 [7], 1931 images representing 45 yoga classes were selected and achieved 83.27% accuracy for pose grading using contrastive skeleton feature representation. In contrast, we have selected 5k images categorized into 107 classes as an enhanced version of Yoga-45. The best accuracy of SYD-Net is 87.17%, rendered by DenseNet-201 with ImageNet weight initialization, reported in Table VIII. However, our method is not directly comparable with Yoga-45 due to the differences in dataset characteristics (*e.g.*, sample size and the number of classes) and experimental setup.

The best top-1 accuracies of SYD-Net on four datasets using Xception, trained from scratch (srth), and ImageNet weights (ImNet) are reported in the last two columns of Table II. The proposed Sports-102 and Dance-12 datasets are publicly available for further improvement and comparative analysis.



Fig. 12. The tSNE plots of SYD-Net on Dance-12 using MobileNet-v2. Left to right: General baseline; Baseline with attention mechanism; SYD-Net with  $P_{25}$ , and finally, SYD-Net with  $P_{30}$ .

Method	Backbone Types	Top-1 Acc	Top-5 Acc
Yoga-82 [8]	MobileNet-V2	71.11	88.50
	ResNet-50	63.44	82.55
	DenseNet-201 variant	79.35	93.47
Ensemble [13]	keypoints + ensmble	80.14	-
Fusion [11]	DenseNet-161 (ImNet)	81.00	-
SYD-Net	ResNet-50	93.92	99.42
	NASNetMobile	94.70	99.60
	DenseNet-201	95.87	99.20
	MobileNet-v2	96.00	99.78
	Xception	97.29	99.42

 TABLE IX

 COMPARISON OF TOP-1 AND TOP-5 ACCURACY(%) ON YOGA-82.

TABLE X Accuracy (%) of Various Key Components of SYD-Net and Random Erasing Augment using MobileNet-v2.

SYD-Net components	Sports	Dance	Par
Using $P_{12}$ only, no attention	89.56	69.78	2.4
Using $P_{20}$ only, no attention	86.94	68.54	2.4
Using $P_{30}$ only, no attention	92.57	80.21	2.4
Spatial attention only: $SA_{12}$	77.18	67.71	3.9
Spatial attention only: $SA_{20}$	77.36	69.07	4.8
Spatial attention only: $SA_{30}$	78.54	69.55	6.1
Channel attention only: $CA_{12}$	91.44	74.88	6.4
Channel attention only: $CA_{20}$	91.53	76.12	6.4
Channel attention only: $CA_{30}$	94.00	77.54	6.4
sigmoid spatial attention: $SA_{12}$	77.62	70.31	3.9
sigmoid spatial attention: $SA_{20}$	93.06	84.89	8.9
sigmoid spatial attention: $SA_{30}$	93.90	85.96	10.2
$P_{12}$ with general dropout	92.46	84.24	7.9
$P_{20}$ with general dropout	93.85	84.83	8.9
$P_{30}$ with general dropout	94.24	86.61	10.2
$P_{12}$ without Gaussian dropout	93.06	83.29	7.9
$P_{20}$ without Gaussian dropout	94.13	84.60	8.9
$P_{30}$ without Gaussian dropout	94.82	85.60	10.2
$P_{30}$ with 1 erased region, rand RGB	94.48	84.89	10.2
$P_{30}$ with 1 erased region, RGB=127	93.69	84.13	10.2
$P_{30}$ with 2 erased regions, RGB=127	94.52	86.43	10.2
P20, 2 erased regions, rand RGB: SYD-Net	94.78	87.73	10.2

paths separately to analyze the effectiveness of attention mechanism in a performance gain. It is evident that the patchbased channel attention (CA) path is more beneficial than the spatial attention (SA) module. The reason could be that feature maps optimization across the channel dimension (MobileNetv2:  $7 \times 7 \times 1280$ ) is more effective over the spatial dimension ( $7 \times 7 \times 2$ ). Because the feature space per patch is larger in cross-channel interaction than in spatial dimension, which ignores discriminative information during feature selection through spatial pooling. Also,  $P_{30}$  achieves better accuracy than  $P_{12}$ , as observed in earlier ablation studies.

2) Different activations in MLP and dropout layers: The effectiveness of softmax over sigmoid activation in the MLP layer of spatial attention is investigated. It is noted that softmax is more efficient in activating the neurons to estimate the probability maps for producing spatial attention masks. However, both activations are useful for improving overall accuracies leveraging the attention mechanism. The contribution of the Gaussian dropout (GD) is tested over the general dropout for regularization. It is evident that GD improves the learning task and enhances accuracy.

3) Variations in random erasing data augmentation: The performance of two randomly selected regions over a single region on input image during image augmentation is tested. The examples of random region erasing are illustrated in Fig. 3. The regions are non-overlapping, and the randomness of

# E. Feature Maps Visualization

The confusion matrices of Dance-12 with  $P_{30}$  are shown in Fig. 11. We have delved into various key layers to visualize feature maps using the t-SNE [70] plots in Fig. 12. The figures show the feature distributions of data separability and clusters to reflect the discriminativeness of SYD-Net features. Here, the Dance-12 test set is considered for summarizing the feature distributions into a smaller subspace for visualization. In Fig. 12, the first two images show a comparison of feature representation between the traditional data augmentation and its improvement using the attention mechanism. Both techniques are considered as baselines. The last two t-SNE figures show feature representations of  $P_{25}$  and  $P_{30}$  in a lower dimension. These figures clearly show the class-wise feature map clusters with a significant class separability over the baselines. Also, the data distribution in  $P_{30}$  is slightly improved over  $P_{25}$ . This difference is reflected in the accuracy.

### F. Ablation Study

The effectiveness of major components of SYD-Net is assessed on Dance-12 and Sports-102 using the MobileNetv2 backbone. Mainly, the ablation study is focused on: (1) the patch-based attention module (PbA) and its sub-components; (2) the significance of two different activations in MLP; and (3) the impact of variations in random erasing data augmentations. The results are reported in Table X.

1) Patch-based attention module and its components: We have evaluated the accuracy of three sets of hybrid patches without any attention module, *i.e.*,  $P_{12}$  (9U+3H),  $P_{20}$ (16U+4H), and  $P_{30}$  (25U+5H) regions. The results imply that the inclusion of patches could improve the accuracy over the baseline performances, given in Table III. Also,  $P_{30}$  renders better accuracy compared to  $P_{12}$  and  $P_{20}$ .

The significance of channel attention and spatial attention mechanisms of SYD-Net are explored. We have tested both related hyper-parameters (e.g., size and color) of both regions are independent. SYD-Net is trained from scratch in two different erasing cases, *i.e.*, one with the random RGB values and another with a fixed RGB=127 value. In this test, we considered only  $P_{30}$  patches using MobileNet-v2. It implies that two erased regions could improve the accuracy compared to one erased region in both cases of RGB values. Because two smaller erased regions can learn more effectively than a larger erased region within the input image and improve the recognition accuracy. Also, random RGB performs slightly better than a fixed value RGB=127. The data augmentation of two erased regions with random RGB values performs more effectively in SYD-Net. Finally, the best model components of SYD-Net rendering the highest performance underlying MobileNet-v2 are given for completeness of ablation studies, implying the suitability of major components of the proposed SYD-Net architecture.

### VI. CONCLUSION

This paper proposes a new patch-based attention method, called SYD-Net for fine-grained human posture recognition. We have introduced and benchmarked two new image datasets, representing 12-dance, and 102-sport actions with diversity. SYD-Net has achieved better performances on the Yoga-82 and Yoga-107 datasets. SYD-Net integrates fixed-size and multi-scale patches to learn contextual information and semantic understanding to define a comprehensive feature descriptor through spatial and channel attention. Random region erasing data augmentation also improves accuracy. Overall evaluation of various key components justifies the contribution of each module of SYD-Net. In the future, we plan to develop larger datasets on Sport and Dance styles and explore graph-based deep architecture for human posture recognition.

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