Knock, knock. Who’s there?–Identifying football player jersey numbers with synthetic data

Divya Bhargavi
Erika Pelaez Coyotl
Sia Gholami

Amazon Web Services, CA USA

Abstract

Automatic player identification is an essential and complex task in sports video analysis. Different strategies have been devised over the years, but identification based on jersey numbers is one of the most common approaches given its versatility and relative simplicity. However, automatic detection of jersey numbers is still challenging due to changing camera angles, low video resolution, small object size in wide-range shots and transient changes in the player’s posture and movement. In this paper we present a novel approach for jersey number identification in a small, highly imbalanced dataset from the Seattle Seahawks practice videos. We use a multi-step strategy that enforces attention to a particular region of interest (player’s torso), to identify jersey numbers. We generate in-house synthetic datasets of different complexities to supplement the data imbalance and scarcity in the samples. Our multi-step pipeline first identifies and crops players in a frame using a pretrained person detection model. We then utilize a pretrained human pose estimation model to localize jersey numbers (using torso key-points) in the detected players, obviating the need for annotating bounding boxes for number detection. This results in images that are on average 20x25px in size. We trained two light-weight Convolutional Neural Networks (CNNs) with different learning objectives: multi-class for two-digit number identification and multi-label for digit-wise detection to compare performance. Both models went through a pre-training round with the synthetic datasets and were finetuned with the real-world dataset to achieve a final best accuracy of 89%. Our results indicate that simple models can achieve an acceptable performance on the jersey number detection task and that synthetic data can improve the performance dramatically (accuracy increase of 9% overall, 18% on low frequency numbers) making our approach achieve state of the art results.

1. Introduction

In recent years, interest in analyzing team sport videos has increased significantly in academia and industry (Ye et al. 2005; Šari et al., 2008; Lu et al., 2013. Gerke et al., 2015; Li et al., 2018. Liu and Bhanu, 2019; Vats et al., 2021). This is important for sports broadcasters and teams to understand key events in the game and extract useful information from the videos. Use cases include identifying participating players, tracking player movement for game statistics, measuring health and safety indicators, and automatically placing graphic overlays. For broadcasters and teams that don’t have the leeway or the capital to install hardware sensors in player wearables, a Computer Vision (CV) based solution is the only viable option to automatically understand and generate insights from games or practice videos. One important task in all sports CV applications is identifying players, specifically

©2022 Divya Bhargavi, Erika Pelaez Coyotl and Sia Gholami.
License: CC-BY 4.0, see https://creativecommons.org/licenses/by/4.0/
identifying players with their jersey numbers. This task is challenging due to distortion and deformation of player jerseys based on the player posture, movement and camera angle, rarity of labelled datasets, low-quality videos, small image size in zoomed out videos, and warped display caused by the player movement. (see Figure 1 and 2)

Current approaches for jersey number identification consist of two steps: collecting and annotating large datasets (Li et al., 2018; Vats et al., 2021), and training large and complex models (Li et al., 2018; Liu and Bhanu, 2019; Vats et al., 2021). These approaches include either sequential training of multiple computer vision models or training one large model, solving for 2 objectives: identifying the jersey number location (through custom object detection models or training a custom human pose estimation model) and classifying the jersey number (Gerke et al., 2015; Li et al., 2018; Liu and Bhanu, 2019; Vats et al., 2021). These approaches are tedious, time-consuming, and cost-prohibitive thus making it intractable for all sports organizations.

In this paper we present a novel approach to detect jersey numbers in a small dataset consisting of practice video footage from the Seattle Seahawks team. We use a three-step approach to number detection that leverages pretrained models and novel synthetic datasets. We first identify and crop players in a video frame using a person detection model. We then utilize a human pose estimation model for localizing jerseys on the detected players using the torso key-points, obviating the need for annotating bounding boxes for number locations. This results in images that are less than 20x25 px with a high imbalance in jersey numbers (see Figure 2). Finally, we test two different learning approaches for model training - multi-class and multi-label each yielding an accuracy of 88%, with an ensemble accuracy of 89% to identify jersey numbers from cropped player torsos.

Additionally, to compensate for the low number of examples in some of the jersey numbers, we propose two novel synthetic dataset generators — Simple2D and Complex2D. The Simple2D generator creates two-digit number images from different combinations of fonts and background colors to mimic those of the Seattle Seahawks jerseys. The Complex2D generator superimposes the Simple2D numbers on random COCO dataset (Lin et al., 2014) images to add more complexity to the background and make the model training robust. By pretraining our two CNNs on these synthetic datasets, we observe a 9% increase in accuracy on the ensemble models pre-trained with synthetic data compared to the baseline models trained with the only the Seattle Seahawks numbers. Furthermore, we observe better generalization with low data.

2. Related work

2.1 Synthetic Data Generation

CNN algorithms, that are commonly used in most CV tasks, require large datasets to learn patterns in images. Collecting and annotating large datasets is a manual, costly and time-consuming task. Several new approaches including Active Learning (Settles, 2009), Zero or Few-shot learning (Larochelle et al., 2008) and Synthetic data generation (De Campos et al., 2009) have emerged in recent years to tackle complexities in obtaining a large annotated dataset. Our work focuses primarily on the use of synthetically generated data. This idea dates back to the 1990’s (Nikolenko et al., 2021) and is an active field of research that alleviates the cost and efforts needed to obtain and manually label real-world
Identifying football player jersey numbers with synthetic data

Figure 1: Example frames from the practice videos demonstrating the challenges to identify jersey numbers in zoomed out videos.

data. Nowadays, models (pre)trained on synthetic datasets have a broad range of utility including feature matching (DeTone et al., 2018) autonomous driving (Siam et al., 2021), robotics indoor and aerial navigation (Nikolenko, 2021), scene segmentation (Roberts et al., 2021) and anonymized image generation in healthcare (Piacentino et al., 2021). The approaches broadly adopt the following process: pre-train with synthetic data before training on real-world scenes (DeTone et al., 2018; Hinterstoisser et al., 2019), generate composites of synthetic data and real images to create a new one that contains the desired representation (Hinterstoisser et al., 2018) or generate realistic datasets using simulation engines like Unity (Borkman et al., 2021) or generative models like GANs (Jeon et al., 2021; Mustikovela et al., 2021). There are limitations to each of these regimes but one of the most common pitfalls is performance deterioration in real-world datasets. Models trained only synthetic datasets don’t generalize to real-world data; this phenomenon is called ”domain shift” (Jeon et al., 2021).

In order to reduce the need for annotating large dataset as well as account for the size and imbalance of the real-world data, we generated two double-digit synthetic datasets - Simple2D and Complex2D with different levels of complexity as described in Section 3.2.2. This helps to circumvent the domain shift when only synthetic data is used and improves generalization on real-world data for fine-tuning.
2.2 Number Identification

Automatic number identification in sports video has evolved from classical computer vision techniques including feature extraction using contrast adjustment, edge detection of numbers (Ye et al., 2005; Šari et al., 2008; Lu et al., 2013) to deep learning-based architectures that use CNNs for classification (Gerke et al., 2015; Li et al., 2018; Liu and Bhanu, 2019; Vats et al., 2021). A fundamental problem in number identification in sports is the jersey number distortion due to erratic and continuous player movement. The spatial transformer-based approach introduced in (Li et al., 2018) tries to localize and better position the number, so that the classifier has a better chance of an accurate prediction. The faster-RCNN with pose estimation guidance mechanism (Liu and Bhanu, 2019) combines the detection, classification and key-point estimation tasks in one large network to correct region proposals, reducing the number of false negative predictions. This approach needed careful labeling of the player bounding-boxes and four human body key-points, shoulder (right, left), hip (right, left), in addition to the numbers. It also made use of high-resolution number images (512 px). This approach yields 92% accuracy for jersey number recognition as a whole and 94% on the digit-wise number recognition task. However, getting the right conditions for it i.e., label the dataset for the three tasks, acquiring high resolution images and training a large model might be challenging for real-world cases. Furthermore, a lack of standardization and availability of public (commercial use) datasets, makes it difficult to obtain a benchmark for the number identification task.
3. Approach

3.1 Task Definition

We define a jersey number as the one or two-digit number printed on the back of a player’s shirt. The jersey number is used to identify and distinguish players and one number is associated with exactly one player. Our solution takes cropped images of player’s torsos as input and attempts to classify the jersey number into 101 classes (0-99 for actual numbers and 100 for unrecognizable images/ jerseys with no numbers).

3.2 American Football Dataset

The data used for this work consisted of a collection of 6 practice videos from different angles for training and additional 4 for testing from the Seattle Seahawks archives. Half of the videos were from the endzone perspective, that is, the scoring zone between the end line and the goal line. The other half were from the sideline perspective, the boundary line that separates the play area from the sides. Both cameras were placed on a high altitude to get a panoramic view for the play and capture the majority of the actions taken by the players. A pitfall for collecting data using this camera angle is that the size of a player is less than 10% of the image size when the players are far away from the camera. In addition, the sideline view has restricted visibility of jersey numbers compared to end-zone (see Figure 3). The videos were recorded in 1280x720 resolution and we sampled frames from each video at 1, 5 and 10 frames per second (fps) rates. We noticed that images sampled at 5 fps sufficiently captured all the jersey numbers in a play and we decided to use the same sampling rate throughout our solution.

![Figure 3: Examples of frames obtained from the two different angles from the training videos. Left, is the endzone view of the players. Right is the sideline view which offers better visibility into jersey numbers. Within a play, we can find players, observers with/without football jerseys.](image)

3.2.1 Jersey number localization

To mitigate the need for annotating player location, jersey number bounding boxes and consequently training person and jersey number detection models, we utilized pretrained
models for person detection and pose estimation to localize the jersey number region. This approach prevents the model to generate correlations with wrong features like player background, helmets or clothing items and confining the learning to the region of interest.

For the number localization we first use a pretrained person detector, Centernet (Duan et al., 2019) model (ResNet50 backbone), to detect and crop players from an image. Instead of training a custom human key-point estimation head (Liu and Bhanu, 2019), we use a pretrained, pose estimation model, AlphaPose (https://gitee.com/marcy/AlphaPose, with ResNet101 backbone), to identify four torso key-points (left and right - hips and shoulders) on the cropped player images from the person detection step (see Figure 7). We use the four key-points to create a bounding box around jersey numbers. To accommodate inaccuracies in key-point prediction and localization due to complex human poses, we increased the size of torso keypoint area by expanding the coordinates 60% outward to better capture jersey numbers. The torso area is then cropped and used as the input for the number prediction models discussed in Section 3.2.2. In previous works, the use of high-resolution images of players and jersey numbers is very common. However, the American football dataset we used was captured from a bird’s eye view, where jersey numbers were smaller than 32x32 px. In fact, the average size of the torso crops is 20x25 with the actual jersey number being even a smaller portion of this area (see Figure 4).

After player detection and jersey number localization, we generated 9,000 candidate images for number detection. We labelled the images with Amazon SageMaker GroundTruth and noticed that 6,000 images contained non-players (trainers, referees, watchers); the pose estimation model for jersey number localization simply identifies human body key-points and doesn’t differentiate between players and non-players. 3,000 labelled images with severe imbalance (see Figure 5) were usable for the training.

### 3.2.2 Synthetic Data Generation

Typically, a licensed (SVHN (Goodfellow et al., 2013)) or a large custom dataset is used for (pre)training number recognition models. Since there are no standardized public datasets with permissive licenses, we created two 2-digit synthetic datasets to pretrain our models. We investigated 2-digit MNIST (Sun, 2019), however it did not have pixel color and font variations needed for jersey detection and performed poorly in our tests. Hence, we generated two different synthetic datasets; a simple two-digit (Simple2D) numbers with font and background similar to the football dataset and other with 2-digit synthetic numbers superimposed on COCO (Lin et al., 2014) dataset images (Complex2D) to account for variations in numbers background.

The Simple2D dataset was generated by randomly selecting a number from a uniform distribution of 0 to 9 and randomly scaling it. Color backgrounds (Red, Navy Blue, Green, Red, Yellow, White) and special font (Freshman) that resembled the team jerseys were used to generate these numbers (see Figure 4). One Light, five Medium and five Hard augmentations (see Table 1) were used on each digit to be later permuted and concatenated to obtain 4000 images (100 x 100 px) of each 2-digit number, from 00 to 99. At the end this dataset consisted of a total of 400,000 images.

Since the real-world images had more complicated background, textures and lighting conditions, we decided to synthetically generate another dataset (see Figure 6) to increase
Figure 4: Distribution of the sizes from person and torso bounding boxes. Note how the great majority of torso sizes is less than 32x32 px.

the robustness and generalization of our pretrained model. The complex2D dataset was designed to increase background noise by superimposing numbers from Sample2D on random real-world images from the COCO dataset (Lin et al., 2014). We generated a total of 400,000 images (4000 per class) with noisy backgrounds. Our algorithm is explained in more details in Algorithms 1, 2 and 3.

Table 1: data augmentations

| Name   | Augmentations                                           |
|--------|--------------------------------------------------------|
| Light  | Gaussian Noise, Optical distortion                     |
| Medium | Light + Grid distortion                                |
| Hard   | Medium + Shuffling RGB channels, Random Shift-Scale-Rotation |
Figure 5: Distribution of the jersey number labels in training set. Number 3 has 500+ images while numbers 43, 63, 69 and 93 have 10 images or less.

Figure 6: Synthetic data generation with Simple2D and Complex2D. Simple2D dataset was generated by creating numbers in football dataset jersey colors and fonts. Several augmentations (Table 1) were applied on these numbers to get Simple2D dataset. The numbers from this dataset were randomly sampled and randomly placed on COCO dataset images to form Complex2D dataset.

3.2.3 Jersey number detection

After the number localization step above, two models were sequentially pretrained with the synthetic datasets (Simple2D to Complex2D) and fine-tuned with the real-world football dataset (see Figure 7). The idea of training a model with increasingly difficult samples is called curriculum learning. This technique has empirically shown accuracy increase and...
forall \( n \) in 0-9 do
  select a jersey background and font color with a probability of \( U(1,n) = \) number of combinations;
  choose a font size with a probability of \( U(a,b) \) if \( a, b \) are scaled factors of image size;
  paste single number with chosen font and background color and size;
end

Algorithm 1: Number generation

forall \( n \) in 0-99 do
 forall background colors do
    generate 1000 images;
    if single digit then
      perform light, medium and hard augmentations;
      scale image to 100x100 px;
    else
      perform light, medium and hard augmentations on each digit;
      concatenate digits;
      scale image to 100x100 px;
    end
  end
end
randomly sample 4000 images per number across all color combinations;

Algorithm 2: Simple2D

forall \( n \) in 0-99 do
  select a random image from COCO dataset;
  select a random jersey number image;
  super-impose jersey number at a random position in the COCO image;
  rescale image to 100x100 px;
  continue until 4000 images per number are obtained;
end

Algorithm 3: Complex2D

faster convergence (Weinshall et al., 2018; Hacohen and Weinshall, 2019). One of the challenges of implementing curriculum learning is manually ranking difficulty in the training set (Weinshall et al., 2018). In our case, the synthetic data was generated explicitly in this manner (simple to complex) and our training regime adopted this order, thus, bypassing this challenge.

Both models used a ResNet50 (He et al., 2016) architecture with deep residual connections, as backbone and a final layer predicting classes (jersey numbers). The first model was a multi-class image classifier to detect two-digit number with a total of 101 different classes (numbers from 0 - 99 plus an unrecognizable class). The second model was a multi-class
multi-label classifier with 21 classes to detect single digits (10 digits for each side—right, left numbers, plus an unrecognizable class).

We define the i-th input feature \( X_i \) (cropped image of a player) with the label \( y_i \) (0-99 for actual numbers and 100 for unrecognizable). Our multi-class model was optimized with the following loss function:

\[
L_{mc} = \sum_i L_i = -\sum_i y_i \log \hat{y}_{mc}(X_i)
\]

where \( y_i \) is the true label and \( \hat{y}_{mc} \) is calculated as a softmax over scores computed by the multi-class model as follows:

\[
\hat{y}_{mc}(X_i) = \sigma(\vec{Z})
\]

\[
\sigma(\vec{Z})_k = \frac{e^{z_k}}{\sum_{j=0}^{100} e^{z_j}}
\]

Where \( \vec{Z} \) is the outputs from the last layer of the multiclass model consists of \( (z_0, ..., z_{100}) \) given \( X_i \).

For the multi-label model, the loss function is defined as:

\[
L_{ml} = \sum_i L_i = -\sum_i y_i \log \hat{y}_{ml}(X_i)
\]

where \( y_i \) is the true label and \( \hat{y}_{ml} \) is calculated as a sigmoid over scores computed by the multi-label model as follows:

\[
\hat{y}_{ml}(X_i) = \frac{1}{1 + e^{-\vec{Z}}}
\]

Where \( \vec{Z} \) is the outputs from the last layer of the multilabel model given \( X_i \).

Both models were trained until convergence and the model from the epoch with the best performance was selected. We explored the combination of the two models to provide the final decision and we explain our results in section 4. Our original idea was that the multi-label model would augment performance of the multi-class model and address generalization issues with unseen/low data availability for certain numbers. For example, if 83, 74 were present in the training set but not 73, the right and left side of prediction nodes for 3 and 7 would have been activated in the train set for all numbers starting and ending with 7 or 3 and hence the multi-label model would have enough samples to predict 73.

We considered training a custom object detection model to identify single-digit numbers. However, due to additional cost and time associated with labeling bounding boxes, image quality and small size of localized jersey numbers (approximately 20 x 25 px), we chose the image classification approach.

4. Experimental Results

We trained the ResNet50 multi-class(number-detection) and multi-label(digit-detection) jersey number classifiers on the football dataset to establish baseline performance without the
Identifying football player jersey numbers with synthetic data

Figure 7: Overview of the approach for extracting data, training and generating jersey number predictions. a) describes the high-level football dataset processing pipeline - identify person in video, pass each person image through pose estimation model to identify torso region and crop them. b) shows the sequential pretraining of multi-class/label models with synthetic number datasets - Simple2D and Complex2D as well as fine-tuning on football dataset. c) represents the inference pipeline that uses data pipeline from a) to crop jersey numbers and perform prediction using multi-class/label models Figure b)

For the multi-class model, we took the number with highest softmax score as the prediction. For the multi-label model, we applied a threshold of 0.5 to both right and left predicted classes to get the output. Eventually we computed the final prediction from the output of the two models.

The baseline model accuracy was 80% for both models. We experimented with various input image sizes and found optimal accuracy at 224x224 px for the multi-class and 100x100 px for the multi-label model. Our dataset presented a high imbalance across several numbers where 24% of the numbers have less than 100 samples and only 5% reach the 400-sample mark (See Figure 3). Hence, we duplicated data points for each number to have 400 images in the training set when needed. Our training pipeline dynamically applies image augmentation so that no image is seen twice by the models, even when the base image is the same. We also up sample our test-set images to maintain 20 images per number.

After having our baselines, we investigated the effects of pre-training with the generated synthetic data on our model performance. Pre-training on the Simple2D dataset and fine-tuning on the football dataset, resulted in a performance improvement of 2% over the baseline (82%), for both, multi-class and multi-label models. However, pre-training on the Complex2D dataset and fine-tuning on the football dataset, resulted in 3% improvement on the multi-class model and 8% on the multi-label model. By pre-training on both Simple2D...
and Complex2D, we achieved 8.8% and 6% improvement above the baseline in multi-class and multi-label models respectively.

The best multi-label model (Complex2D + Football dataset) had positive accuracy improvements on 74 classes, no change in accuracy in 19 classes, negative change in accuracy in 8 classes (drop by 10%). The best multi-class model (Simple2D + Complex2D + Football dataset) had positive accuracy improvements on 63 classes, no change in accuracy in 21 classes, negative change in accuracy in 17 classes (drop by 7%). In order to validate the hypothesis (Section 3.2.3) that multi-label model could have better performance on numbers with less images, we compare its results with best multi-class model on numbers with less than 50 images in training set. We notice an average increase in accuracy of 18.5% for multi-class model and 20% for multi-label model before and after training on synthetic data, for these numbers. Despite larger gains in accuracy shown by multi-label model, the absolute accuracy scores for these numbers were better for multi-class model, 81% compared to 78% for multi-label model.

By analyzing the confusion matrix of the model predictions, we learnt that the best multi-label model produces false predictions in 2 major scenarios (see Figure 8): predicting one digit rather than both digits, and predicting class 100 for low-resolution and hard-to-recognize digits. In other words, the multi-label model is more likely to predict one digit number and non-number classes when challenged with new data. The multi-class model, however, has relatively spread-out false predictions (see Figure 9). Major areas of error for this model are: predicting one digit rather than both digits, and mistaking single digits for two digits or unrecognizable class.

Examining the performance of the two models independently we noticed that predictions agree in 84.4% of the test cases, suggesting that despite the different objectives (multi-class vs multi-label) there is a robust learning of the number representations. Furthermore, we notice an additional improvement of 0.4% by two-model ensemble. Table 2 presents our results.

Figure 8: Images where multi-label predicted class 100. The multi-label model is not sure of the number class when the input image has very low resolution.
Table 2: A comparison of model performance under different conditions with confidence threshold of 0.5

| Experiment                                | Multi-class | Multi-label | Ensemble |
|-------------------------------------------|-------------|-------------|----------|
| Without synthetic data                    |             |             |          |
| Football dataset                          | 0.8064      | 0.8         |          |
| Best (Multi-class + Multi-label)          |             |             | 0.8028   |
| With synthetic data pre-training          |             |             |          |
| Simple2D + Football dataset               | 0.8282      | 0.82        |          |
| Complex2D + Football dataset              | 0.8306      | 0.88        |          |
| Simple2D + Complex2D + Football dataset   | 0.8886      | 0.86        |          |
| Best (Multi-class + Multi-label)          |             |             | 0.8931   |

5. Limitations

The work presented in this paper shows that the number identification task can be simplified by leveraging synthetic datasets. We were able to obtain a good performance that is comparable with previous works (Ye et al., 2005; Šari et al., 2008; Gerke et al., 2015) requiring no change in the data collection pipeline. Despite these findings, we recognize this approach has some limitations which we describe in this section.

We were able to achieve 89% accuracy for our test dataset regardless of the challenging nature of jersey number identification in a low-data regime. This performance is on par with some of the most recent works (Vats et al., 2021). However, the lack of a benchmark dataset for this task and unavailability of already implemented tools, is a big barrier for comparing performance across all methods. The only solution is to label large amounts of high-quality data and retrain the available solutions in-house. This requires a lot of
computational resources and man-hours put into work, which is not always an option for all institutions.

In our jersey detection models, we used ResNet50 as a base model, because it proved to be effective for this task. Bigger and more sophisticated models might provide better accuracy and recall but an exhaustive search is necessary for each of the components of the solutions to determine an optimal cost-benefit tradeoff. We recognize that more investigation is needed here to determine such optimal.

In our solution we chose a three-model pipeline approach versus a one-pass prediction model. Our approach comes with a few limitations including cascading inaccuracies from one model to the next and increase in latency. However, our choice was justified by ease of implementation, maintenance and portability to other domains. Even with this cascading effect, our solution proves to have a good performance in our highly imbalanced, limited dataset.

6. Future Work

Our approach to increase performance can be broadly classified into two categories: improving data quality and quantity or experimenting with different models.

6.1 Data quality and quantity

We observed no improvement in model accuracy by increasing the number of duplicated samples or the number of image augmentations. The confidence of the predictions directly correlated with the quality and resolution of the jersey number crop (input image). In future work, we plan to experiment with various image quality enhancement methods in classical CV and deep learning domains to observe if it improves performance. Another path that can be considered is to refine our synthetic data generation pipeline to produce images that are closer to the real-world dataset.

6.2 Different model strategies

Our current method has minimal labeling effort. However, by collecting more images of reasonable quality and quantity we plan to test object detection-based models. One way to improve frame level accuracy would be to track detected jersey numbers across both side-line and end-zone views so that in situations where numbers are partially visible or player pose is complex, we would be able to obtain predictions with continuity. Tracking players in team sports like football is still a major challenge in the sports CV domain and we will evaluate its utility in our future work.

7. Conclusion

This paper presented a new solution for low-data regime jersey detection with two-stage novel synthetic data generation techniques, pose estimation for jersey number localization and CNN ensemble learning to detect jersey numbers. Data augmentations during training and the use of large synthetic dataset provided enough variations for the model to generalize well and learn numbers. Our solution is easy to implement, requires minimal labeling,
curation, supervision, and can be customized for various sports jersey fonts, colors and backgrounds. Our framework improves the accuracy of number detection task by 9% and can be easily extended to similar tasks across various Sports communities as well as industries with similar use cases. Furthermore, our solution did not require the modification of the data capturing or processing pipeline that is already in place, making it convenient and flexible.

Additionally, it introduces a novel data synthesis technique that can boost custom solution performance in a wide array of sports. We hope this solution enables the Sport Analytics community to rapidly automate video understanding solutions.

References

S. Borkman, A. Crespi, S. Dhakad, S. Ganguly, J. Hogins, Y.-C. Jhang, M. Kamalzadeh, B. Li, S. Leal, P. Parisi, et al. Unity perception: Generate synthetic data for computer vision. arXiv preprint arXiv:2107.04259, 2021.

T. E. De Campos, B. R. Babu, M. Varma, et al. Character recognition in natural images. VISAPP (2), 7:2, 2009.

D. DeTone, T. Malisiewicz, and A. Rabinovich. Superpoint: Self-supervised interest point detection and description. In Proceedings of the IEEE conference on computer vision and pattern recognition workshops, pages 224–236, 2018.

K. Duan, S. Bai, L. Xie, H. Qi, Q. Huang, and Q. Tian. Centernet: Keypoint triplets for object detection. In Proceedings of the IEEE/CVF international conference on computer vision, pages 6569–6578, 2019.

S. Gerke, K. Muller, and R. Schafer. Soccer jersey number recognition using convolutional neural networks. In Proceedings of the IEEE International Conference on Computer Vision Workshops, pages 17–24, 2015.

I. J. Goodfellow, Y. Bulatov, J. Ibarz, S. Arnoud, and V. Shet. Multi-digit number recognition from street view imagery using deep convolutional neural networks. arXiv preprint arXiv:1312.6082, 2013.

G. Hacohen and D. Weinshall. On the power of curriculum learning in training deep networks. In International Conference on Machine Learning, pages 2535–2544. PMLR, 2019.

K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 770–778, 2016.

S. Hinterstoisser, V. Lepetit, P. Wohlhart, and K. Konolige. On pre-trained image features and synthetic images for deep learning. In Proceedings of the European Conference on Computer Vision (ECCV) Workshops, pages 0–0, 2018.

S. Hinterstoisser, O. Pauly, H. Heibel, M. Martina, and M. Bokeloh. An annotation saved is an annotation earned: Using fully synthetic training for object detection. In Proceedings
of the IEEE/CVF international conference on computer vision workshops, pages 0–0, 2019.

E. Jeon, K. Kim, and D. Kim. Fa-gan: Feature-aware gan for text to image synthesis. In 2021 IEEE International Conference on Image Processing (ICIP), pages 2443–2447. IEEE, 2021.

H. Larochelle, D. Erhan, and Y. Bengio. Zero-data learning of new tasks. In AAAI, volume 1, page 3, 2008.

G. Li, S. Xu, X. Liu, L. Li, and C. Wang. Jersey number recognition with semi-supervised spatial transformer network. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, pages 1783–1790, 2018.

T.-Y. Lin, M. Maire, S. Belongie, J. Hays, P. Perona, D. Ramanan, P. Dollár, and C. L. Zitnick. Microsoft coco: Common objects in context. In European conference on computer vision, pages 740–755. Springer, 2014.

H. Liu and B. Bhanu. Pose-guided r-cnn for jersey number recognition in sports. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops, pages 0–0, 2019.

C.-W. Lu, C.-Y. Lin, C.-Y. Hsu, M.-F. Weng, L.-W. Kang, and H.-Y. M. Liao. Identification and tracking of players in sport videos. In Proceedings of the Fifth International Conference on Internet Multimedia Computing and Service, pages 113–116, 2013.

S. K. Mustikovela, S. De Mello, A. Prakash, U. Iqbal, S. Liu, T. Nguyen-Phuoc, C. Rother, and J. Kautz. Self-supervised object detection via generative image synthesis. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 8609–8618, 2021.

S. I. Nikolenko. Synthetic simulated environments. In Synthetic Data for Deep Learning, pages 195–215. Springer, 2021.

S. I. Nikolenko et al. Synthetic data for deep learning. Springer, 2021.

E. Piacentino, A. Guarner, and C. Angulo. Generating synthetic ecgs using gans for anonymizing healthcare data. Electronics, 10(4):389, 2021.

M. Roberts, J. Ramapuram, A. Ranjan, A. Kumar, M. A. Bautista, N. Paczan, R. Webb, and J. M. Susskind. Hypersim: A photorealistic synthetic dataset for holistic indoor scene understanding. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 10912–10922, 2021.

M. Šari, H. Dujmi, V. Papi, and N. Roži. Player number localization and recognition in soccer video using hsv color space and internal contours. In The International Conference on Signal and Image Processing (ICSIP 2008). Citeseer, 2008.

B. Settles. Active learning literature survey. 2009.
M. Siam, A. Kendall, and M. Jagersand. Video class agnostic segmentation benchmark for autonomous driving. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 2825–2834, 2021.

S. Sun. Multi-digit mnist for few-shot learning. URL: https://github.com/shaohua0116/MultiDigitMNIST, 2019.

K. Vats, M. Fani, D. A. Clausi, and J. Zelek. Multi-task learning for jersey number recognition in ice hockey. In Proceedings of the 4th International Workshop on Multimedia Content Analysis in Sports, pages 11–15, 2021.

D. Weinshall, G. Cohen, and D. Amir. Curriculum learning by transfer learning: Theory and experiments with deep networks. In International Conference on Machine Learning, pages 5238–5246. PMLR, 2018.

Q. Ye, Q. Huang, S. Jiang, Y. Liu, and W. Gao. Jersey number detection in sports video for athlete identification. In Visual Communications and Image Processing 2005, volume 5960, pages 1599–1606. SPIE, 2005.