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Crown-Centric Disguise Classification In Yakshagana Imagery Using Deep Learning Techniques

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Abstract

Yakshagana, a theatrical art form in Karnataka, has variants like Thenku-thittu, BadaguThittu and Badaabadagu Thittu. Research explores its history, contemporary impact, and makeup trends. The Tenkutittu Yakshagana features different kinds of crowns. The type of crown the performer wears dictates the choice of disguise. For the purpose of disguise identification in this study, we have primarily examined classes such as kesaritatti, kolu kirita, pakdi, and kuttari. Therefore, this paper explores the use of deep learning methods for masking categorization in Yakshagana images, such as YOLOv5 and Three Tier CNN. A Cyclic Gate Recurrent Neural Network has been employed to classify Shaiva and Vaishnava characters. Following the categorization of the characters, the model is determining the disguise. Three-tier CNN classifies disguises with an accuracy of 85%. After conducting tests and assessments, it was concluded that YOLOv5, which has a 96% accuracy rate in identifying several items in an image, is the best appropriate algorithm for disguise categorization. Crown-Centric Disguise identification is a real-time tool that assists novices in determining which kind of crown and disguise a certain Yakshagana figure should wear.

Index terms— *Yakshagana, Crown Detection, YOLOv5 , Three tier Convolution Neural Network (CNN), Object detection, Disguise Classification, Cyclic Gate Recurrent Neural Network (CGRN)*

1 Introduction

Yakshagana, an ancient traditional theatrical art, known as Bayalaata in Kannada, is deeply rooted in the coastal districts of Karnataka [1] [2]. It's also referred to as Thenku-thittu in parts of Kerala and Dakshina Kannada, and BadaguThittu in Udupi and Uttara Kannada districts, enjoying widespread popularity in these regions [3]. Research on Yakshagana primarily delves into its historical co[1]ntext, contemporary significance, and cultural impact [4]. While some studies briefly explore makeup and costume trends, the focus remains modest [5]. To fully understand Yakshagana, character classification, crown identification and facial pattern analyis is essential, as each character possesses a unique style of dress and makeup [6]. Standardized

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disguise types in Yakshagana are easily distinguishable by their clothing and makeup, making it accessible to audiences [7]. This article takes a technological approach, employing machine learning techniques such as YOLOv5 and Three-tier CNN to identify specific disguise [8]. This fusion of tradition and technology contributes to the preservation and wider recognition of Yakshagana in today's world [9]. In this study, the accuracy and processing time of these two types of CNN architectures in the context of disguise classification and identification in Yakshagana images [10].

The absence of an automated system for character classification and actor recognition in Yakshagana is leading to time-consuming and subjective processes with potential inaccuracies. This lack of technological support hinders accessibility for newcomers and jeopardizes the preservation and promotion of Yakshagana as a cultural heritage, especially among younger generations [11-15]. To address these challenges, this research develop an automated system using machine learning techniques to accurately classify Yakshagana disguises based on crown types. Following are several contributions arising from the proposed work:

- This article discusses deep learning methods, such as YOLOv5 and Three tier CNN for disguise identification in Yakshagana images.
- The proposed methods has been implemented on python and its efficiency is analyzed using metrics such as precision, accuracy and F1 score.

2 Related works

In 2023, Anantha Murthy, et al [21] have experimented object detection using SSD and its benefits over other object identification techniques. The network, as visible on the feature map, modifies the default boxes to better reflect the shape of the items, and scores are derived by the number of times an item category occurs inside each box during prediction. Many feature maps with varying resolutions are employed, and the result is blended to aid in the management of objects of various sizes. Additionally, SSD is applied for crown identification in Yakshagana photos. In 2022, Tingting Liang et al [22] have did CBNet: Composite Backbone Network Architecture for Object Detection. Researchers offer CBNet, an innovative and flexible backbone architecture Under the pre-training fine-tuning paradigm to build high-performance detectors. In 2021, Haijun Zhang et al [23] have executed an empirical study of multi-scale object detection in high resolution UAV images. This research offers MOHR, large-scale benchmark dataset targeted at conducting multi-scale object recognition in high-resolution UAV photos, as well as an empirical study comparing six state-ofthe-art deep learning-based object recognition models. In 2023, Anantha Murthy, et al [24] have provided a overview of the study that uses several Convolutional Neural Network (CNN) methods to detect objects. This study's main objective is to use CNNs for automatic object detection, which includes tasks like confirming an object's presence, locating it precisely, and estimating its size. Object detection has several applications in robotics, autonomous vehicles, and surveillance, among other fields. In 2019, Padmanabha K. V and Dr. Sathish Kumar [25] have did a research on Yakshagana's contemporary themes that include experimentation and relevance. The current conceptual article looks at these experiments as interpolated themes, folk, historical, imaginative, social, local temple tales, and awareness-oriented topics. It analyzes how these projects have been received critically by the public, artists, and academics. In this study, we aim to identify disguises based on the specific crowns worn by the performers.

3 Methodology

The Proposed Methodology focus on disguise Classification based on crown types in Yakshagana Images Using Machine Learning Techniques. This methodology involves Data collection, Preprocessing, Feature extraction, classification. Block diagram of disguise Classification based on crown types is shown in figure 1.

3.1 Disguise classification based on crown types

Yakshagana performers follow a specific order for selecting their attire. Each character uses distinctive crowns aiding in their identification. Disguise categorization centers around different types of crowns the artists uses and the make up patters the performer follows. There are approximately 15 types of crowns featured in the Tenkutittu Yakshagana. The choice of disguise is determined by the specific crown worn by the performer. For instance, the character portraying Devi exclusively wears the DeviMudi, while those in Rajavesha are adorned with the Kolu Kireeta. Bannada Vesha performers may opt for either the Kesari tatti or the Bheema Mudi. Hennubanna is characterized by the exclusive use of the Kuttari crown, Pundu Vesha allows for either the Pakdi or Turai, Naatakeeya Vesha presents the option of either the Peta or Naatakeeya Kireeta, and Shtreevesha is identified by the Kirana crown. Specific crown types used by performers can be found in Table1 with its description as referenced in the research.

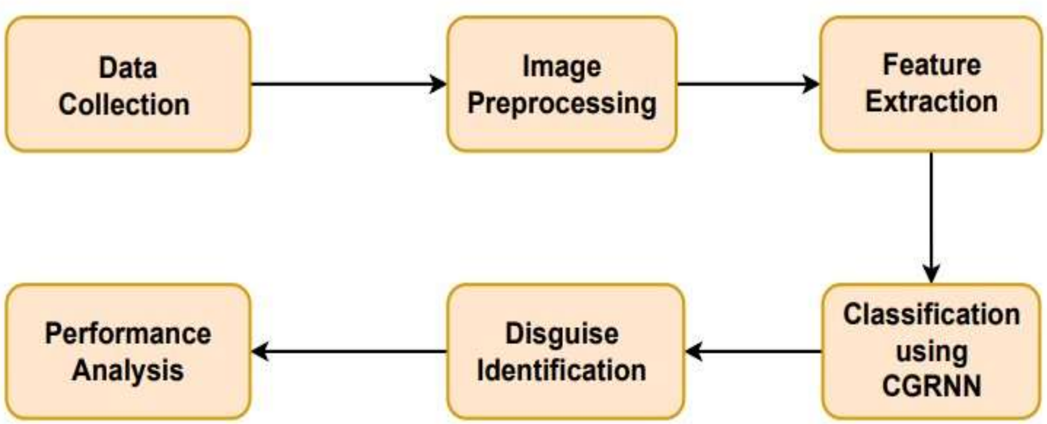

Figure 1: Block diagram of disguise Classification

3.1.1 Data collection

The dataset consists of a real-time photo file. Approximately 10,000 distinct crown kinds are included in the manually gathered dataset. The collection of Yakshagana images encompassing diverse patterns were compiled and objects frequently observed during Yakshagana performances. When generating the dataset, augmentation techniques such as rotation range = 30, zoom range = 0.2, and brightness between 0.6 and 0.7 were used. We have taken into consideration a ratio of about 80:20 for the training and testing of the data. After data collection is complete, the data is labeled with appropriate limits so that it may be easily identified. The model's accuracy will be improved with the help of the labeled data. Next, the data must undergo pre-processing in order to improve its quality.

3.1.2 Preprocessing using Multigrid Ensemble Kalman Filter

In preprocessing the images are preprocessed by removing noise from input dataset and for this the Multigrid Ensemble Kalman Filter (MEKF) [12] is used and it uses a sequential data assimilation technique that estimates a state variable at time U_H^S by integrating an initial estimate, a collection of observations, and a linear dynamical model for removing noise and enhancing the image qualities. The collective approximation of error covariance matrix reduces the processing resources needed by the fine grid $U^S_{(H-1)}$ an examined solution is utilized to remove the noiseby using U_H^S in equation (1).

$$\left(U_H^S\right)^s = Q_{h:h-1}^S\left(\left(U_{H-1}^S\right)^E, \theta_H^{-e}\right) \tag{1}$$

Where θ_H^{-e} denotes ensemble average of coarse-level parameter. Coarse grid state is updated in this stage. If no observations are available, this update, denoted U_H^E, is generated using conventional iterative processes on the coarse grid and starting solution $(U_H^E)'$. If observations are available, Kalman gain matrix $(H_H^E)^{u,c}$ is calculated via MEKF utilized to enhance image quality $(K_H^E)^n$ through a MEKF operation in equation (2).

$$(U_H^E)' = (U_H^E) + (H_H^E)^{u,c}\left[(Z_H^E)^n - (K_H^E)^n\left((U_H^E)\right)\right] \tag{2}$$

Crown	Name	Description
	Devi Kireeta (Mudi)	Characters belonging to the devi category, such as Devi, Vishnu, Bhoodevi, Laxmi, etc., wear crowns of this type.

	Naatakeeya Kireeta	Characters like Bali, Hiranyakashyap, Kamsa, Ravana, and so on wear crowns of this kind. This falls into a category of rakshasa disguise.
	Peta	This type of crown is used for minister-type characters
	Pakdi	This type of crown is used for young-aged characters like Abhimanyu, Agni, Varuna, Vayu, etc. This falls under Punduvesha disguise Category.
	Kesari Thatti	Characters such as Shumbha, Nishumbha, Raavana, Taarakasura, and so on wear crowns of this kind. belongs to the category of Bannada Vesha.
	Turayi	Prahlad, Lava, Kusha, Subrahmanya, Brahma, Vishnu, etc. are among the deities who wear crowns of this kind fits within the Punduvesha group.

	Bheemana Mudi	Particularly for roles like Bheema, Dushyasana, Ghatothkaj, Kumbhakarna, etc., this kind of crown is utilized. belongs to the Bannadavesha group.
	Kuttari	Belongs to the Hennubanna category and is utilized for Shoorpankha, Taataki, Hidimbi, etc.
	Dharmarayana Kireeta	Suitable for Rajavesha category (Dharmaraya, Sugreeva, Hamsadhwaja, etc.)
	Hanumanthana Kireeta	Used only for Hanuman character
 	Kirana	Belongs to the Sthreevesha category and is used for all female roles.
	Kolu Kireeta	Characters like Arjuna, Devendra, Rakthabeeja, Hiranyaksha, and others fall under the category of Rajavesha.

Table 1: Notable Crown Types

3.1.3 Feature Extraction using Adaptive with concise empirical wavelet transform

Feature Extraction is a technique for breaking down the dimensionality of image, or "dimensions," into digestible bits. For this Adaptive with concise empirical wavelet transform (ACEWT) [13] is utilized reduce image features for the required dimensions. The power spectral density is displayed the distribution with frequency in whichZ(l)is The Fourier transform of the signal and its average power R may be written as following equation (3).

$$R = \lim_{L\to\infty} \frac{1}{2L} \int_{-L}^{L} Z(l)^2 \, \mathrm{dl} \tag{3}$$

The power spectral density expressed in equation (4),

$$F_{zz}(s) = \lim_{L\to\infty} A \left[\left| \hat{Z}_L(s) \right|^2 \right] \tag{4}$$

Using the above equation the Feature is reduced by breaking down the dimensionality of input image into digestible bits for the classification of disguises based on crowns using Cyclic Gate Recurrent Neural Network in the following section.

3.1.4 Image Classification using Cyclic Gate Recurrent Neural Network

The Cyclic Gate Recurrent Neural Network (CGRNN) [14] is a customized neural network used for Vaishnava and Shaiva character classification. CGRNN aids in the selection of which is the actual character in the given image. The character classification is done by analyzing several images, which is assisted by the use of the equation (5).

$$\mathrm{Maxi} J_3 = \frac{1}{E_p} \sum H_{\mathrm{Res}} \left(E_j \right) \tag{5}$$

$$\phi(R) = \frac{\mathrm{mod}(R - w, R)}{R} \tag{6}$$

3.2 Disguise Identification using YOLOv5 and Three tier CNN

The goal of this study is to dissect the differences between these two algorithms, focusing on their application to the classify the disguises based on crown type.

3.2.1 Three tier CNN for Disguise identification

For the classification of Vaishnava or Shaiva pictures, a deep image classifier uses a 3-tier convolutional neural network [16]. For class probabilities, it employs softmax activation and RGB channels. For classification, the characteristics flow into thick layers, improving stability and performance as shown in equation (7).

$$\mathrm{QI}(S) = \mathrm{GO}\left(\mathrm{SE}\big(\mathrm{BER}(S)\big)\right) + \mathrm{GO}\left(\mathrm{SE}\big(\mathrm{BQR}(S)\big)\right) \qquad (7)$$

Here Sis input data map,"BER" is Global Average Pooling,"BQR" Global Max Pooling,"GO" Batch Normalization. Several of works, depth-first spatial next sequential organization performed best and is shown in equation (8).

$$Q(S) = \sigma\big(Q_I(S) + Q_F(S)\big) \qquad (8)$$

When constructing, it may incorporate the depth-wise attention $Q_I(S)$ and spatial attention $Q_F(S)$ modules in a variety of ways and through which the Character is identified successfully using the three-tier CNN architecture.

3.3 YOLOv5 for Disguise Identification

The traditional one-stage object detection algorithm is YOLO [15]. The detection issue is now a regression issue. It uses regression method to directly calculate bounding box coordinates probability of every class. The average aggregation and the maximum aggregation are then linked after the Y"pool" layer decreases tensor of first dimension to second dimension. TheY-"pool" is characterized by equation (9).

$$Y - \mathrm{pool}(U) = [\mathrm{Maxpool}_{\mathrm{ni}}(U), \mathrm{avgpool}_{\mathrm{ni}}(U)] \qquad (9)$$

After that, the batch normalization layer and the conventional convolution layer with a kernel size of U are applied to the reduced tensor, and the rotated tensor is then given the attention weight of the appropriate dimension produced by the sigmoid function. The three branches' combined outputs are added together as one in the equation (10).

$$z = \frac{1}{3}\left(\overline{\hat{u}_1\sigma\left(\varphi_1\big(\hat{u}_{1_\square}\big)\right)} + \overline{\hat{u}_2\left(\varphi_2\big(\hat{u}^{\square_1}\big)\right)} + u\sigma\left(\varphi_3\big(\hat{u}^{\square_3}\big)\right)\right) \qquad (10)$$

This process is repeated for each scale, and the final output is a list of bounding boxes and their corresponding class probabilities for each pattern detected in the image was detected successfully and more accurately using YOLOv5 when compared with the Three tier CNN.

3.4 YOLOv5 and Three tier CNN experimental comparison

In the first experiment, the networks accessed using the closed subset issue for face categorization. It don't allow any face pictures from Yakshagana frames to enter the network's input, therefore it don't require any confidence or thrash classes, making this task simpler than open classification and claim the result as state-of-the-art because no trials were conducted on the Yakshagana picture collection. In this experimental comparison, the pattern recognition capabilities of two well-known object detection models were investigated using, YOLOv5 and Three tier CNN. The goal is to ascertain which model is more effective in spotting and identifying patterns in Yakshagana pictures. Here is a high-level overview of the experimental setup.

3.5 Performance Analysis

After that the Model is selected using two object detection models, namely YOLOv5 and Three tier CNN, is used for their proficiency in accomplishing diverse object detection assignments. Then its Model is trained using a GPU-accelerated deep learning framework like TensorFlow or PyTorch, and both models on the Yakshagana dataset was trained. During training, the model is fed examples from the training set, its parameters are adjusted, and its hyper parameters are optimized using methods like grid search and Bayesian optimization. Then the Model is evaluated by the metrics like precision, accuracy, and F1 score to assess how well they perform on the testing set. These indicators evaluate how well the models can spot and identify Yakshagana visual patterns. Then it is Compared and Analyzed the performance of the two models, considering metrics like accuracy, precision, F1 score, and their generalization capabilities to new patterns and objects beyond the training set. Notably, YOLOv5 outperforms Three-tier CNN in terms of classification accuracy when compared to existing methods. Hyperparameter values of CNN are shown in Table 2.

CNN Parameter	**Values**
Number of Convolutional Layers	3
Number of Filters	64
Filter Size	3x3
Stride	1
Pooling	Max
Number of Fully Connected Layers	2
Dropout	0.5
Learning Rate	0.001
Batch Size	32
Number of Epochs	100
Activation Function	ReLU

Table 2: CNN Hyperparameters

4 RESULTS AND DISCUSSION

This section presents the results of an experiment on crown-centric disguise identification. The Precision-Confidence curve, F1-Confidence Curve and Recall-Confidence curve are depicted below. It can be observed that a state-of-the-art result in differentiating between four different classes of crowns (Kesaritatti, Kolu Kireeta, Pakdi, or Kuttari) is achieved by experimenting with the yakshagana images shown in figures 2-7. The graph's categories for all classes are the result of combining four classes.

Figure 2: Result of identification of disguise using YOLOv5

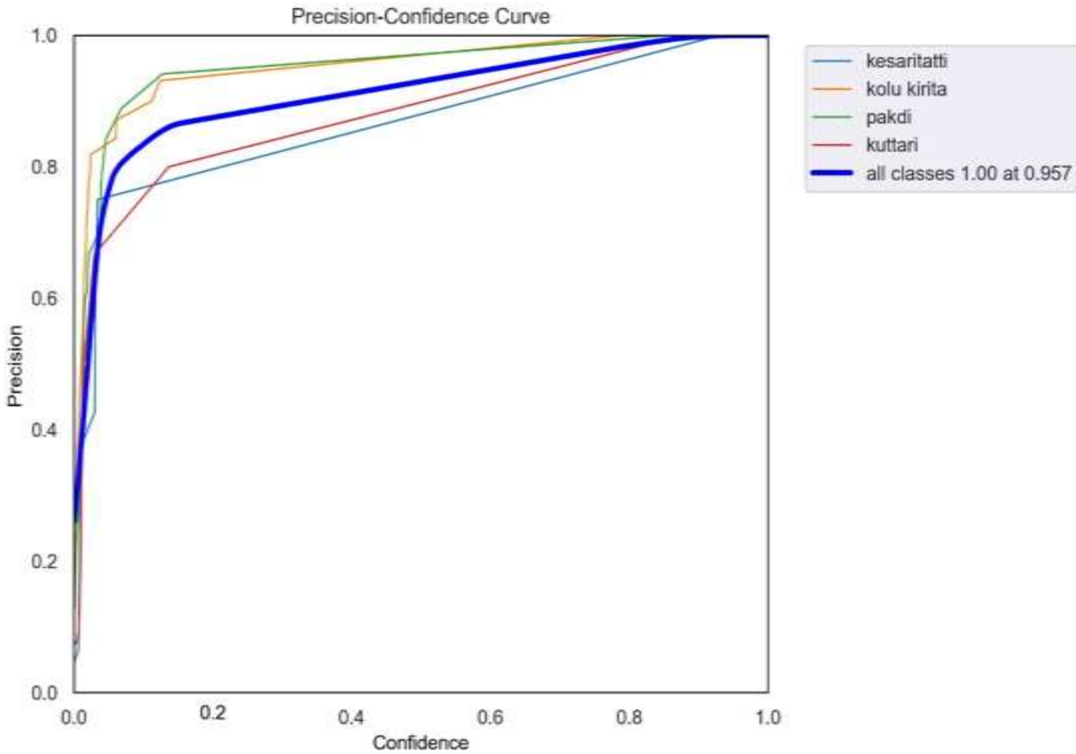

Figure 2: Precision v/s Confidence Curve

Figure 4: Result of identification of disguise using YOLOv5

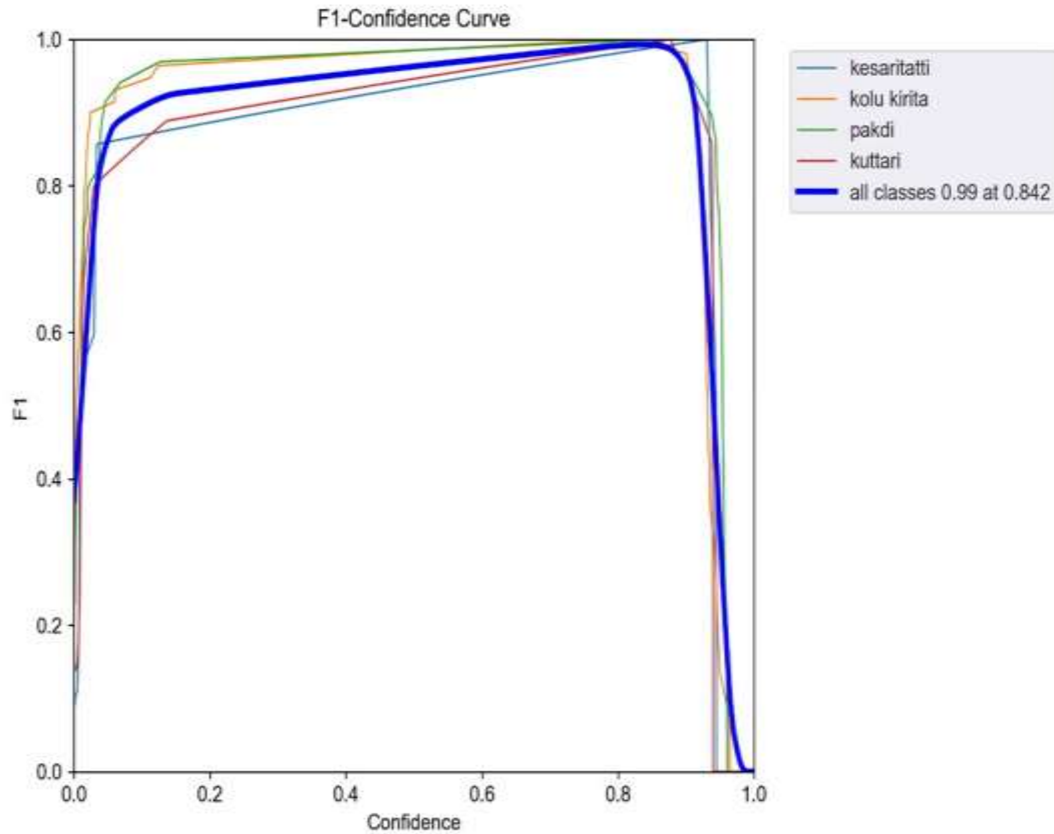

Figure 5: F1-Confidence Curve

Figure 6: Result of identification of disguise using CNN

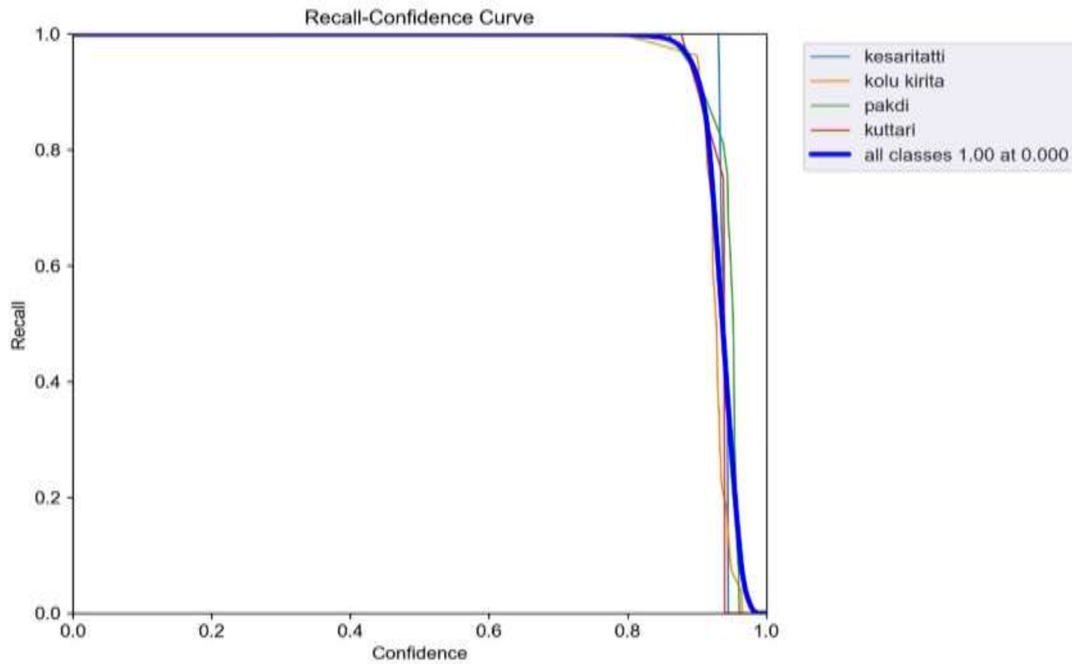

Figure 7: Recall-Confidence Curve

4.1 Performance Analysis

The performance of the two models strengths and weaknesses is compared and analyzed using metrics such as accuracy, precision,F1 score. Also it is shown in the following table.The evaluation metrics reveal that YOLOv5 has higher precision compared to the three-tier CNN , indicating better accuracy in classifying the disguises based on crown types. YOLOv5 significantly outperforms the three-tier CNN in F1 score (96% vs. 85%). In terms of efficiency, YOLOv5 processes images much faster (0.057 ms on average) compared to the three-tier CNN (1.39 seconds on average), highlighting a substantial efficiency gap. Additionally, processing time does not vary with image size for either algorithm.

Algorithm	**Category of Class**	**Precision (%)**	**Accuracy (%)**	**F1-Score (%)**	**Recall (%)**
YOLOv5	Kesaritatti	95.7	98.2	95	94.1
	Kolu Kireeta	94.7	97.4	96	93.7
	Pakdi	95.8	98.0	93	95.9
	Kuttari	95.2	90.3	94.6	95.02

Three Tier CNN	Kesaritatti	84.27	85	85.4	84.4
	Kolu Kireeta	83.86	87	87	84.02
	Pakdi	84.4	83	84	85.06
	Kuttari	85	82	80	85.7

Table 3: Performance Metrics for Algorithms

4.2 Classification performance comparison

This is investigated in order to assess performance of suggested method. Following confusion matrix is, True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN), for Accuracy, precision, F1 score is shown below in equations (1), (2), and (3).

$$Precision = \frac{TP}{FP + TP} \tag{11}$$

$$Recall = \frac{TP}{TP + FN} \tag{12}$$

$$F1Score = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall} \tag{13}$$

5 CONCLUSION AND FUTUREWORK

For disguise categorization based on crown type identification in Yakshagana images, machine learning algorithms like YOLOv5 and Three-tier CNN have produced promising results. In summary, YOLOv5 achieves an efficiency of 96% accuracy in disguise categorization, outperforming the threetier CNN. These outcomes highlight the advantages of every approach in their corresponding fields. When it comes to disguise classification, YOLOv5 is unique because of its quick inference time, high accuracy in identifying several crown objects in a single image, and simple architecture that makes training and development easier. It is particularly good at distinguishing faces and crown characteristics that are necessary to recognize distinct disguises in Yakshagana images. However, the choice of machine learning algorithm and architecture depends on specific requirements, including dataset size, image complexity, and available hardware resources.To increase these algorithms' precision and effectiveness in practical Yakshagana disguise categorization analysis applications, more study and development are required. Extending the set of classes under consideration could lead to improved disguise recognition in the future and allow for the creation of a model that can identify disguises and crowns in real-time while streaming videos. This development attempts to educate viewers and accommodate those who are curious about the art.

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