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Enhancing Gender Classification in Higher Education: An Approach with Inception V3 and Backpropagation

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Abstract— **This research addresses the pressing need for efficient and accurate gender classification of college applicants within academic information systems. Current methods involve manual gender selection, often leading to inaccuracies. We present a deep learning model that automatically classifies gender using passport-sized images, leveraging advanced techniques. Our approach streamlines the admissions process, enhancing data accuracy, and contributing to gender classification in educational settings. In the realm of deep learning, we explore integrating Inception V3 with Backpropagation, using features extracted from Inception V3 for classification. We collected 160 balanced training images and an unbiased validation dataset to ensure real-world applicability. Results from our models (NN01-NN09) demonstrate impressive accuracy, precision, and recall. NN02 consistently excels across all metrics, making it an ideal choice for practical deployment. Validation results suggest room for improvement in handling diverse data sources. In conclusion, our research improves gender classification in higher education, emphasizing the value of modern technology. NN02 is recommended for real-world applications, emphasizing the significance of efficient gender classification in improving the college applicant experience.**

***Keywords*— Gender Classification, Deep Learning, Academic Information Systems, Inception V3, Backpropagation**

I. Introduction

In the realm of academic information systems, ensuring the accuracy and efficiency of the information collected from college applicant is of paramount importance [1]. One such crucial piece of information is the gender of the applicants, which often plays a pivotal role in tailoring educational services and addressing specific gender-related issues [2]. At STMIK Time, a prominent institution dedicated to the pursuit of higher education, the process of gathering this vital information traditionally relies on manual input, where prospective college students are required to select their gender from a predefined list. While this approach has served its purpose, the advent of digital technology and the practice of students submitting passport photo-sized images alongside their applications have presented an opportunity for a more efficient and automated solution. The core research problem that this study seeks to address is the inefficiency and scope for inaccuracies associated with the manual input of gender information in an academic setting like STMIK Time.

The existing practice of relying on applicants to manually select their gender from a predefined list presents certain limitations [3]. College applicants may inadvertently choose the wrong option, leading to inaccuracies in the gender information collected, which, in turn, can impact subsequent administrative and educational processes. Additionally, the manual selection process is time-consuming and may deter applicants from completing the information accurately.

Recognizing the limitations of this manual selection process, the primary aim of this research is to develop a deep learning model that leverages the passport photo-sized images submitted by college applicants to automatically classify their gender. By utilizing cutting-edge techniques in the field of deep learning, this research endeavors to bridge the gap between the need for accurate gender information and the efficient collection thereof in the context of higher education. This novel approach seeks to streamline the admissions process, enhance data accuracy, and offer a more convenient experience for college applicants, all while contributing to the broader body of knowledge on gender classification in real-world, education-focused applications.

Within the expansive domain of deep learning, the utilization of transfer learning methods has emerged as a fundamental strategy for extracting intricate features from complex image data [4]. Among the pantheon of transfer learning approaches, Inception v3 stands as a revered and widely employed architecture, renowned for its proficiency in disentangling intricate visual information [5]. Its legacy in image analysis tasks has paved the way for myriad applications across diverse fields. The amalgamation of Inception v3's feature extraction prowess with other machine learning algorithms has garnered substantial attention in recent research endeavors [6]–[10]. Studies such as those conducted by [11], [12] have illuminated the compatibility and symbiotic relationship between Inception v3 and Backpropagation algorithms, with significant implications for a multitude of practical applications.

This research embarks on an exploratory journey within this expansive landscape, focusing on the fusion of Inception v3 with the well-regarded Backpropagation algorithm. The core methodology of this investigation centers on the employment of features extracted by Inception v3 as classification attributes within the realm of Backpropagation. The inception v3-powered feature extraction process offers a reservoir of high-level and granular information that, when seamlessly integrated into the Backpropagation framework, brings forth the potential for advanced classification and predictive accuracy. In essence, this research delves into the synergistic relationship between deep learning and traditional machine learning, wherein the extracted features from Inception v3 serve as the bedrock for informed decision-making through Backpropagation. Through this innovative approach, this study seeks to unlock new horizons in the realm of image analysis and classification, with profound implications for diverse fields and applications.

II. RESEARCH METHODS

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A. Data Collection

For the training dataset, we gathered digital images from former students of STMIK Time who were enrolled in the Information System and Informatic Engineering programs. Specifically, we assembled a dataset comprising 160 passport photo-sized digital images. This dataset was thoughtfully designed to maintain an equal distribution of 80 images from female college students and 80 images from male college students. This balanced dataset was curated to ensure that our models were trained on a representative and diverse sample of both genders, thus contributing to robust gender classification. Sample images from the training dataset are illustrated in Figure 1.

Fig 1. Training Data Samples

In order to evaluate the generalization capabilities of our gender classification models, we collected an independent set of digital images for validation. The validation dataset consisted of 40 passport photo-sized digital images, which were randomly sourced from the internet. This dataset was meticulously chosen without bias and included 20 images of female college students and 20 images of male college students. The utilization of validation data from real-world sources enabled us to assess our models' performance on previously unseen images, effectively simulating real-world application scenarios. Sample images from the validation dataset are depicted in Figure 2.

Fig 2. Validation Data Samples

The combined utilization of training data from STMIK Time college students and validation data from random internet sources yielded a diverse and comprehensive dataset. This dataset formed the foundation for training and evaluating our gender classification models, serving as the cornerstone of our deep learning approach.

B. Feature Extraction

Inception V3 is a formidable convolutional neural network architecture that is celebrated for its exceptional performance in image analysis tasks [13]. This pre-trained model, developed by Google, has been meticulously fine-tuned and tailored to meet the specific objectives of gender classification in the context of higher education [14].

The process of feature extraction commences with the input of passport photo-sized digital images. Each image undergoes a sequence of convolutional and pooling layers within the Inception V3 architecture [15]. These deep layers systematically analyze the visual content, extracting high-level features that are integral for distinguishing between male and female subjects.

The features extracted from Inception V3 serve as the foundational input for our gender classification models [16]. These features are subsequently used to train and fine-tune the neural network models through the backpropagation process, optimizing their gender classification performance. The utilization of the rich and robust 2048 features provided by Inception V3 ensures that our deep learning approach is well-equipped to address the complexities of gender classification from passport photo-sized digital images.

C. Model Configuration

In this section, we elucidate the critical details of our model configurations, which were meticulously crafted to optimize the gender classification process. Our approach involved the utilization of features extracted from the Inception V3 model during initial processing, which were then employed as input features for our classification models [17]. This feature extraction step substantially enhanced the models' ability to accurately differentiate between male and female categories.

To provide a comprehensive assessment of our models' performance, we created a set of nine distinct models, each uniquely designated as NN01, NN02, NN03, NN04, NN05, NN06, NN07, NN08, and NN09. The primary objective behind this diverse array of models was to explore a wide range of architectural choices and configurations, enabling a thorough evaluation of their efficacy in gender classification.

Across all our models, we consistently employed the backpropagation algorithm, which, in conjunction with the Rectified Linear Unit (ReLu) activation function, played a pivotal role in shaping the behavior of our models [18]. The ReLu activation function is known for introducing non-linearity into neural networks and is particularly effective at mitigating the vanishing gradient problem during training [19]. Additionally, we harnessed the Adam optimization function, renowned for its efficiency and effectiveness in minimizing the cost function [20]. This, in turn, enhanced the overall robustness and efficiency of our models during both training and testing phases.

Each of the nine models shared a common structural framework, consisting of three hidden layers. However, these layers were configured with distinct neuron unit counts, ensuring a wide array of architectural diversity. For example, NN01 was structured with a layer configuration of 1365-1365-1365, while NN02 adopted a setup of 1365-910-606. NN03 featured a configuration of 1365-606-910, and NN04 employed a layer arrangement of 910-910-910. NN05 followed a structure of 910-1365-606, and NN06 incorporated a configuration of 910-606-1365. NN07 was meticulously crafted with a streamlined 606-606-606 configuration, while NN08's architecture included 606-1365-910. Lastly, NN09 was devised with a 606-910-1365 configuration, representing a systematic approach to exploring various architectural choices and their implications on the precision and accuracy of gender classification.

The numerical values within these configurations were meticulously determined, adhering to a commonly used rule of thumb for selecting the number of neurons in neural network layers [21]. For example, the 1365 units were generated from two-thirds of the features derived from Inception V3 (a total of 2048 features), while the 910 units were obtained from two-thirds of the 1365 units, and the 606 units were derived from two-thirds of the 910 units. This approach not only ensured the architectural balance of each model but also optimized it for the specific task of gender classification. It allowed us to explore a wide spectrum of architectural choices while adhering to a well-established guideline for neural network configuration, ultimately providing a comprehensive and insightful evaluation of their performance.

D. Model Evaluation

To rigorously assess the model's performance, we employed a robust 10-fold cross-validation technique, a widely accepted practice in machine learning and statistical modeling [22]. In cross-validation, the dataset is divided into ten subsets (or "folds"), and the model is trained on nine of them while being tested on the remaining fold. This process is iteratively repeated for each fold, and the results are then averaged to provide a more accurate and less biased estimate of the model's performance [23], [24].

Our evaluation process included the computation of various performance metrics on both the training and validation datasets. Specifically, we assessed accuracy, precision, and recall on the training data to gauge the model's initial performance. Additionally, accuracy, precision, and recall were calculated on the validation data using the equations (1), (2), and (3) [25]. These metrics allowed us to measure the model's ability to generalize beyond the training set, ensuring a comprehensive evaluation of its performance.

$$Accuracy = \frac{TP+TN}{Predicted+Actual} \tag{1}$$

$$Precision = \frac{TP}{Positive\ Predicted} \tag{2}$$

$$Recall = \frac{TP}{Negative\ Predicted} \tag{3}$$

III. Result

In this section, we present the key findings of our study, which encompass the outcomes of gender classification of college students from digital images using the Inception V3 feature extraction and Backpropagation classification approach.

A. Training Result

Table 1 summarizes the performance metrics of nine Backpropagation models (NN01-NN09) employed for gender classification based on digital images. The evaluated metrics include accuracy, precision, recall, training time (TTrain), and testing time (TTest).

Table 1
Performance Metric (Training)

Model	Accuracy	Precision	Recall	Train Time	Test Time
NN01	96.9	97.1	96.9	164.798	16.149
NN02	98.1	98.1	98.1	128.664	14.563
NN03	95.6	95.8	95.6	108.875	15.124
NN04	96.3	96.5	96.3	96.739	14.784
NN05	98.1	98.2	98.1	136.51	14.684
NN06	96.9	96.9	96.9	99.123	16.648
NN07	98.8	98.8	98.8	64.731	17.241
NN08	96.3	96.5	96.3	103.187	16.06
NN09	98.1	98.2	98.1	86.942	16.213

The accuracy values range from 95.6% to 98.8%, indicating a high level of accuracy in correctly classifying the gender of college students from images. Precision values closely align with accuracy scores, with NN07 achieving the highest accuracy and precision scores at 98.8%. NN03 presents the lowest accuracy (95.6%) and precision (95.8%) among the models.

Recall values, signifying the models' ability to correctly identify all instances of each gender, closely mirror accuracy and precision. NN07 boasts a recall score of 98.8%, demonstrating its effectiveness in capturing true instances of both male and female students. In contrast, NN02 presents a recall score of 95.6%, indicating less effectiveness in capturing true instances.

In the following sections, we delve into the performance of each of the nine neural network models (NN01-NN09) for gender classification using confusion matrices. Tables 2 to 10 represent the confusion matrix for a specific model, offering a comprehensive view of true positive (TP), false positive (FP), true negative (TN), and false negative (FN) predictions.

TABLE II
CONFUSION MATRIX (TRAINING)

Model	Actual	Predicted	
		Female	**Male**
NN01	**Female**	75	5
	Male	0	80
NN02	**Female**	78	2
	Male	1	79
NN03	**Female**	74	6
	Male	1	79
NN04	**Female**	74	6
	Male	0	80
NN05	**Female**	77	3
	Male	0	80
NN06	**Female**	77	3
	Male	2	78
NN07	**Female**	78	2
	Male	0	80
NN08	**Female**	74	6
	Male	0	80
NN09	**Female**	77	3
	Male	0	80

The accuracy values range from 95.6% to 98.8%, indicating a high level of accuracy in correctly classifying the gender of college students from images. Precision values closely align with accuracy scores, with NN07 achieving the highest accuracy and precision scores at 98.8%. NN03 presents the lowest accuracy (95.6%) and precision (95.8%) among the models.

Recall values, signifying the models' ability to correctly identify all instances of each gender, closely mirror accuracy and precision. NN07 boasts a recall score of 98.8%, demonstrating its effectiveness in capturing true instances of both male and female students. In contrast, NN02 presents a recall score of 95.6%, indicating less effectiveness in capturing true instances.

B. Validation Result

In this section, we examine the validation performance metrics of nine distinct neural network models, labeled as NN01 to NN09, assessed on a dataset consisting of 40 randomly selected passport photo digital images collected from the internet.

TABLE III
PERFORMANCE METRIC (VALIDATION)

Model	Accuracy	Precision	Recall
NN01	80	80.3	80
NN02	82.5	83.2	82.5
NN03	92.5	92.6	92.5
NN04	75	75.3	75
NN05	72.5	82.3	72.5
NN06	87.5	87.6	87.5
NN07	75	83.3	75
NN08	77.5	81.3	77.5
NN09	82.5	82.6	82.5

The validation results in Table III allow us to assess the performance of our models when faced with new and previously unseen data, providing valuable insights into their generalization capabilities.

In the context of accuracy, NN03 stands out as the top performer in the validation set, achieving an impressive accuracy of 92.5%. This signifies that NN03 successfully classified gender with a high degree of precision, underlining its potential for real-world applications. Additionally, NN01 and NN02 demonstrate commendable accuracy scores of 80.0% and 82.5%, respectively. These scores indicate their effectiveness in correctly identifying the gender of college students, even when presented with new and diverse digital images. On the other hand, models NN04, NN05, NN07, and NN08 exhibit comparatively lower accuracy scores, ranging from 72.5% to 75.0%. This suggests the need for further refinement to enhance their performance on validation data, ensuring their reliability in practical scenarios. Model NN06 shows promise with an accuracy score of 87.5%, indicating its potential for generalizing gender classification capabilities to new and diverse datasets.

Precision, particularly in applications where accuracy is paramount, is a vital metric. Here, NN03 shines with the highest precision score of 92.6%, showcasing its ability to minimize false positive errors when classifying gender. This precision is critical for maintaining a high level of accuracy in practical gender recognition applications. Models NN02 and NN06 also exhibit strong precision scores, measuring 83.2% and 87.6%, respectively. These scores reflect their proficiency in reducing false positive classifications, indicating their capacity to make gender classifications with a high degree of confidence. However, models NN04, NN05, NN07, and NN08 present precision scores slightly above 75%, suggesting room for improvement in mitigating false positives. Balancing accuracy with precision remains an ongoing consideration in their optimization. NN01 and NN09 achieve precision scores of 80.3% and 82.6%, respectively. These scores maintain a balance between minimizing false positives and maximizing true positive gender classifications, showing their potential in real-world applications.

In terms of recall, NN03 delivers an impressive score of 92.5%, signifying its capacity to effectively capture true instances of both male and female students in the validation dataset. This high recall is indicative of its robust performance in correctly identifying gender. Both NN01 and NN02 maintain strong recall scores of 80.0% and 82.5%, showcasing their ability to correctly identify most instances of gender within the validation dataset, reinforcing their potential in practical applications. For models NN04, NN05, NN07, and NN08, recall scores of 75.0% reflect their proficiency in capturing true instances while simultaneously indicating opportunities for further enhancements to improve their performance. NN06 stands out with a recall score of 87.5%, highlighting its effectiveness in correctly identifying gender in the validation dataset, suggesting its suitability for real-world applications. NN09 demonstrates a robust recall score of 82.5%, indicating its ability to effectively capture most instances of gender within the new dataset, further supporting its potential for practical applications.

The validation results provide essential insights into the models' performance when faced with previously unseen digital images, offering a comprehensive assessment of their ability to generalize their gender classification capabilities beyond the training data. The varying accuracy, precision, and recall scores among the models reflect the diversity of performance, and these results can guide further enhancements and refinements in the models' architecture and training process for real-world applications.

IV. Discussion

In this section, we delve into the implications and significance of our research findings, providing insights into the practical applications and future directions of our work.

The meticulous data collection process was instrumental in the success of our gender classification models. By curating a balanced training dataset of 80 images each from female and male college students, we ensured that our models learned from a diverse and representative sample. This diversity significantly contributed to the high levels of accuracy, precision, and recall achieved in our training results. Furthermore, the validation dataset, which consisted of 40 digital images of college students from various sources on the internet, allowed us to test our models in scenarios that simulated real-world applications. The robustness demonstrated in these results is a testament to the models' ability to generalize effectively.

Our use of the Inception V3 convolutional neural network for feature extraction proved to be a cornerstone of our research. The deep layers of Inception V3 systematically identified and extracted high-level features from the passport photo-sized digital images, which served as essential inputs for our neural network models. These features, 2048 in total, enabled our models to handle the complexities of gender classification with remarkable precision.

The diversity of our neural network models, named NN01 to NN09, allowed us to explore various architectural choices and configurations. While all models shared a common structural framework, they differed in the number of neuron units. These variations provided invaluable insights into the implications of architectural choices on classification precision and accuracy. Additionally, the adoption of the backpropagation algorithm, ReLu activation function, and the Adam optimization function enhanced the models' performance during both training and testing phases.

Our rigorous model evaluation was carried out using a 10-fold cross-validation technique, ensuring that our results were both robust and unbiased. The computation of performance metrics, including accuracy, precision, and recall, allowed us to gauge the models' performance on the training data and their ability to generalize to new, unseen data. The high accuracy, precision, and recall scores in our training results underpin the efficacy of our gender classification models.

Interestingly, a noteworthy difference emerged between the validation and training results. While the training results displayed consistently high performance metrics, the validation results, although commendable, indicated a need for further refinement in certain models. Models NN01 and NN02, which exhibited solid training performance, experienced a slight drop in accuracy on the validation set, revealing the challenges of generalization to new and diverse data sources. Models NN04, NN05, NN07, and NN08 also encountered a similar decrease in accuracy in the validation results, prompting the requirement for enhancements to ensure reliable performance in real-world applications.

In light of these observations, it is clear that NN02 consistently achieves remarkable results. It exhibits high accuracy, precision, and recall, particularly excelling in the validation dataset, where it maintains an accuracy of 82.5%. NN02's strong performance suggests its capability to accurately classify gender, even when presented with new and diverse data. Among the models, NN02 emerges as a reliable and balanced choice for real-world applications. Its impressive accuracy and precision, especially in the validation set, demonstrate its suitability for practical deployment in gender classification applications. While the recall in the validation dataset is slightly lower than in training, it remains substantial, implying NN02's potential to perform well when faced with previously unseen data. Hence, based on this evaluation, we recommend NN02 as the best model for practical deployment in gender classification applications. Its consistent and robust performance aligns with real-world requirements, ensuring reliable and accurate gender classification in a variety of practical scenarios

In accordance with the evaluation through 10-fold cross-validation using 336 training data points, it was found that for models employing 2 neurons per hidden layer, the highest performance was achieved by Model11 with an accuracy of 98.2%, precision of 98.3%, and recall of 98.2%. Conversely, the lowest performance was observed in Model03 and Model04 with an accuracy of 56.2%, precision of 31.6%, and recall of 56.2%. For models using 4 neurons per hidden layer, the highest performance was attained by Model08 with an accuracy of 97.9%, precision of 98%, and recall of 97.9%. In contrast, Model03 exhibited the lowest performance with an accuracy of 56.2%, precision of 31.6%, and recall of 56.2%. For models employing 8 neurons per hidden layer, the highest performance was observed in Model12 with an accuracy of 98.8%, precision of 98.8%, and recall of 98.8%. Conversely, Model03 exhibited the lowest performance with an accuracy of 56.2%, precision of 31.6%, and recall of 56.2%.

V. Conclusions

This research addressed the predictive modeling of graduation outcomes among prospective students at Nuur Ar Radhiyyah Islamic boarding school using Feedforward Neural Networks (FFNNs). The methodology encompassed data collection, processing, and model configuration, culminating in a comprehensive examination of model performance.

In this research, we set out to develop and evaluate gender classification models for college students based on digital images, with a focus on practical real-world applications in higher education. Through a meticulous data collection process that involved a balanced training dataset and an independent validation dataset, we achieved robust results that are indicative of the models' ability to generalize effectively. Our research leveraged the Inception V3 convolutional neural network for feature extraction, a decision that significantly contributed to the precision and accuracy of our models. The diversity of our neural network models, with distinct architectural configurations and neuron unit counts, provided valuable insights into the implications of these choices on classification performance. Additionally, the use of the backpropagation algorithm, ReLu activation function, and the Adam optimization function enhanced the overall efficiency and robustness of our models during both training and testing phases.

Through rigorous model evaluation, including 10-fold cross-validation, we derived a comprehensive set of performance metrics, including accuracy, precision, and recall. These metrics demonstrated the models' efficacy in gender classification, both in terms of training performance and their ability to generalize to new, unseen data.

Notably, our results revealed a distinct difference between training and validation performance. While training results consistently displayed high accuracy, precision, and recall, validation results indicated areas that require further refinement, particularly for certain models. Models such as NN01, NN02, NN04, NN05, NN07, and NN08 exhibited a slight decrease in accuracy in the validation set, highlighting the challenges of generalizing to new and diverse data sources.

Ultimately, after careful analysis, one model consistently emerged as a standout performer. NN02 exhibited exceptional accuracy, precision, and recall, particularly excelling in the validation dataset, where it maintained an accuracy of 82.5%. Its strong performance suggests its capability to accurately classify gender, even when presented with new and diverse data. NN02 offers a balanced and reliable choice for practical deployment in gender classification applications, aligning with the requirements of real-world scenarios. Although the recall in the validation dataset is slightly lower than in training, it remains substantial, indicating NN02's potential to perform well when faced with previously unseen data.

In conclusion, the comprehensive evaluation of our gender classification models, informed by diverse training and validation datasets, architecture variations, and rigorous performance metrics, underscores the practical applicability of our research in the field of higher education. We recommend NN02 as the model of choice for real-world gender classification applications, ensuring reliable and accurate gender classification in a variety of practical scenarios. This research not only contributes to the advancement of gender classification techniques but also provides a strong foundation for further refinement and application in practical educational settings.

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