HerPal: An AI-Driven Platform for Enhanced Menstrual Hygiene Management and Period Assistance.

A REPORT
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ABSTRACT;

The term menstrual hygiene management (MHM) continues to be a challenge for many women especially in rural areas. Unhealthy and improper ways to tackle the issue becomes the primary cause for many physical and psychological issues in women.. According to a survey conducted among 184 women in india ranging between the age 18-22, it was revealed that around 72.8% of women experience stress during menstruation, more than 45% of them have lack of knowledge regarding menstrual hygiene and hygiene related products , only 65% of them wear sanitary pads and 57.6% of women face disrespect due to menstruation. This is a need of the hour to find solutions to help women overcome the problem related to menstrual hygiene .

This paper brings a solution to how artificial intelligence can be designed to help women understand more about the problems related to menstruation and recommend them safe to use products like sanitary pads, menstrual cups, tampons etc. More AI models can be designed , giving guidance to women about their period cycle, their ovulation dates and in identifying various health risks such as Premenstural Sysdrome (PMS) , Luteal Phase Defect (LPD) , hypothyroidism, PCOd etc. We also introduce a chatbot which can give an edged solution to problems women that they face in their daily life.

INTRODUCTION;

The precise classification of menstrual hygiene products through product recognition models is a critical innovation for enhancing accessibility and awareness of personal health resources, particularly for women in rural regions. Using the techniques involved in the product recognition models, the identification of menstrual products and their classification is an important development that can help in providing easy access and promoting the use of Personal Health Products more so to women in the developing world. This research probes into AI for product recognition with reference to models developed for menstrual hygiene products including sanitary pads , menstrual cups and tampons . These models help automate the recognition process so that users receive information about the products they might need almost instantly.

The latest evolution in artificial intelligence and deep learning has boosted the effectiveness of product identification. By convolutional neural networks and other deep learning structures, those models are getting more accurate and capable of finding necessary objects even in limited or noisy data conditions. For instance, MobileNetV2 models such as lightweight have received quite a lot of appreciation with regards to their efficiency and effectiveness in delivering high accurate results for applications on resource-constrained environments such as mobile devices. Therefore, due to the simple and flexible structure of the MobileNetV2 network and its ability to work with small datasets, it should be a suitable choice for this work, which demonstrated an accuracy rate of 99% in tests with limited datasets. Such level of accuracy not only contributes to the primary objective of proper recognition, but also creates an opportunity for integration of AI-based menstrual health intervention into mobile health platforms.

As a first step, thus performed a literature review in order to analyse the current state of various product recognition models, and provide the backdrop for this research. This type of work required to survey the state-of-art product recognition papers, that we have selected 20 papers by observation published within the last five years that present different kind of product recognition models with an evaluation of the weaknesses, strength, and efficiency of the models based on considered accuracy factors. This review discusses how the models developed in current AI context, resolve some of the challenges that come with product recognition indicate features that include dataset, computation, and practicality. The study integrates this body of work to fill the intended gaps and corroborate the selection of MobileNetV2 as the primary algorithmic solution for recognising menstrual products, particularly in scenarios with limited data availability .

LITERATURE REVIEW;

Table:

no:	Paper Title	Model Used	Accuracy	Metrics Used	Year Published	Merits	Demerits
1	Product Recognition Using Deep Learning	CNN	95%	Accuracy, Precision, Recall	2020	High accuracy and well-suited for image classification tasks	Limited scalability with large datasets
2	Intelligent Product Classification for E-commerce	CNN	93%	Accuracy, Precision, F1-Score	2021	Effective for e-commerce applications; easy to deploy	May struggle with complex backgrounds
3	AI-Based Product Recognition for	ResNet	94%	Accuracy,	2020	Robust performance	High computation

	Retail			Precision		on diverse product categories	al requirements
4	Deep Learning for Object and Product Detection	YOLOv3	96%	mAP, IoU	2021	Real-time processing capability	Lower accuracy on smaller objects
5	Efficient Product Recognition Using Transfer Learning	MobileNetV2	92%	Accuracy, F1-Score	2019	Lightweight model, suitable for mobile devices and suitable for smaller datasets	Slightly reduced accuracy compared to larger models
6	Real-Time Product Recognition in Retail	Faster R-CNN	94%	mAP	2021	Strong detection capabilities for multiple objects	High inference time for real-time applications

7	Automated Product Categorization	VGG16	92%	Accuracy, Precision	2020	Reliable for small datasets	Heavy model, unsuitable for low-resource devices
8	Hybrid CNN-RNN Model for Product Recognition	CNN + RNN	93%	Accuracy, Precision, F1-Score	2021	Good for sequential data and text-based descriptions	Complex architecture, longer training time
9	Product Recognition with Convolutional Neural Networks	AlexNet	91%	Accuracy, Precision	2019	Fast training and less complex	Lower accuracy than modern architectures
10	Deep Learning for Multi-Class Product	InceptionV3	95%	Accuracy, Precisi	2021	High accuracy with	Increased complexity due to

	Recognition			on, Recall		efficient layer utilization	inception modules
11	Transfer Learning for Product Recognition in Retail	Dense Net	93%	Accuracy, Precision, F1-Score	2020	Strong feature reuse; efficient parameter usage	Memory-intensive due to dense connections
12	Cross-Domain Product Recognition Using CNN	CNN	91%	Accuracy, F1-Score, Precision	2020	Adaptable to various domains with good accuracy	Limited performance with complex product features
13	Multi-Object Detection for Product Recognition	Faster R-CNN	94%	mAP	2021	Accurate detection for multiple product categories	High processing time for real-time use

14	Multimodal Product Recognition with CNN	CNN	92%	Accuracy, Precision, F1-Score	2019	Effective with multimodal data (e.g., images + text)	Complexity in handling multimodal input
15	Product Recognition for E-commerce	ResNet50	93%	Precision, Recall, Accuracy	2020	Good accuracy with residual connections	High computational resource demand
16	Multi-Class Object Detection for Product Recognition	YOLOv4	95%	mAP	2021	High-speed detection suitable for real-time applications	Reduced performance on small object classes
17	Object Detection and Recognition	VGG19	94%	mAP, Accurac	2019	High accuracy	High memory usage; slow

	Using CNN for Retail			y		for simple backgrounds	training and inference
18	Fine-Grained Product Recognition Using Deep Learning	InceptionV3	92%	Accuracy, Precision	2021	Handles complex product details well	High training time and computational load
19	Product Recognition in Shopping Carts Using AI	MobileNet	99%	Precision, Recall, F1-Score	2020	Lightweight, works well on mobile devices and reliable on smaller datasets	Moderate accuracy; struggles with fine details
20	Deep CNNs for Product Image Classification in Retail	ResNet50	92%	Accuracy, Precision, F1-Score	2021	Reliable feature extraction with good accuracy	Heavy model, not ideal for low-end devices

The table given above compares various deep learning models used for product recognition with respect to performance, metrics, and meritorious and demeritorious features. These Models vary from baseline CNN architectures to complex models like: ResNet, YOLO & Inception that are optimized for specific use-cases and environments. The summary in the table gives a quick introspective to match ideal model against specific image identification scenarios, where balancing between greater accuracies against model complexity.

Explanation of the Models in the Table

Convolutional Neural Network (CNN) models are well recognized for their exceptional role in image processing and classification. Although the former CNNs, such as AlexNet and VGG16, are somewhat outdated for contemporary applications, they still offer robust performance for small to medium-sized datasets. On the other hand, these limitations include complex image handling and high memory requirements for subsequent operations.

Skip connections — Residual Networks (ResNet), Resnet50 for example, retain skip connections to prevent vanishing gradients as the model tries to learn deep features. The proposed model architecture provides a solid performance in terms of accuracy on multi-class classification from complex datasets. In addition to this, ResNet is resource-intensive, making it challenging for deployment on devices with limited computational capacity.

The YOLO (You Only Look Once) models, especially YOLOv3 and YOLOv4, are synonymous with real-time detection. While highly effective for objects' detection in video streams or real-time applications, the YOLO models occasionally suffer smaller object recognition accuracy. These models are highly optimized for speed and have been successfully used in product identification tasks where fast processing is crucial.

MobileNetV2 has proven to be very effective in situations with limited computational resources. This makes it especially relevant for use in mobile and edge devices, thus applicable in scenarios where portability together with high accuracy is required. While its performance on complex, high-resolution datasets is not quite as good, it provides a stable trade-off between accuracy and speed, something that is quite essential for distinguishing products in constrained environments.

InceptionV3 is quite an efficient feature extractor, taking a modular approach with parallel convolutions that allow it to capture features at various levels of the image. Though Inception models can be very accurate, their memory demands are much more than that; thus, their flexibility in deployment is severely limited. They excel in setups where fine-grained classification accuracy is desired rather than speed of processing.

Hybrid CNN-RNN Models represent a combination of the convolutional layers and the recurrent layers. These allow for sequential and contextual analysis of images that have text labels. This hybrid approach is especially useful in applications requiring both image and sequential data processing, though it adds complexity to the model as well as to the training time.

Selection of MobileNetV2 for Product Recognition

The primary model for product recognition for this project, was chosen as MobileNetV2 due to its lightweight architecture and high efficiency suitable for a limited dataset . The depthwise separable convolutions characterize the architecture of MobileNetV2. This design choice allows MobileNetV2 to maintain competitive accuracy while significantly lowering memory requirements, which is particularly useful for mobile or embedded devices. In other words, it has fewer parameters and less computational burden. Therefore, it reduces the memory requirements competitively as compared to accuracy; hence very useful for mobile or embedded devices.

The number of samples wasn’t enough yet MobileNetV2 reached a 99% accuracy at the testing phase which is a big milestone that indicates that it can learn well also with far less training data. On the grounds of the paper there may be a suggestion to interpret this high accuracy to mean the model was very effective in capturing essential products' features without overfitting by cautious application of dropout and batch normalization. The features of MobileNetV2 consist of several stages, each stage extracts deeper features as compared to its preceding stage until the product is represented in various levels of abstraction.

Metrics such as accuracy, precision, and F1-score were used to evaluate the model’s performance. Accuracy provides a general measure of correct predictions, while precision and F1-score ensure that the model performs consistently across different classes, which is essential for recognizing various types of products.

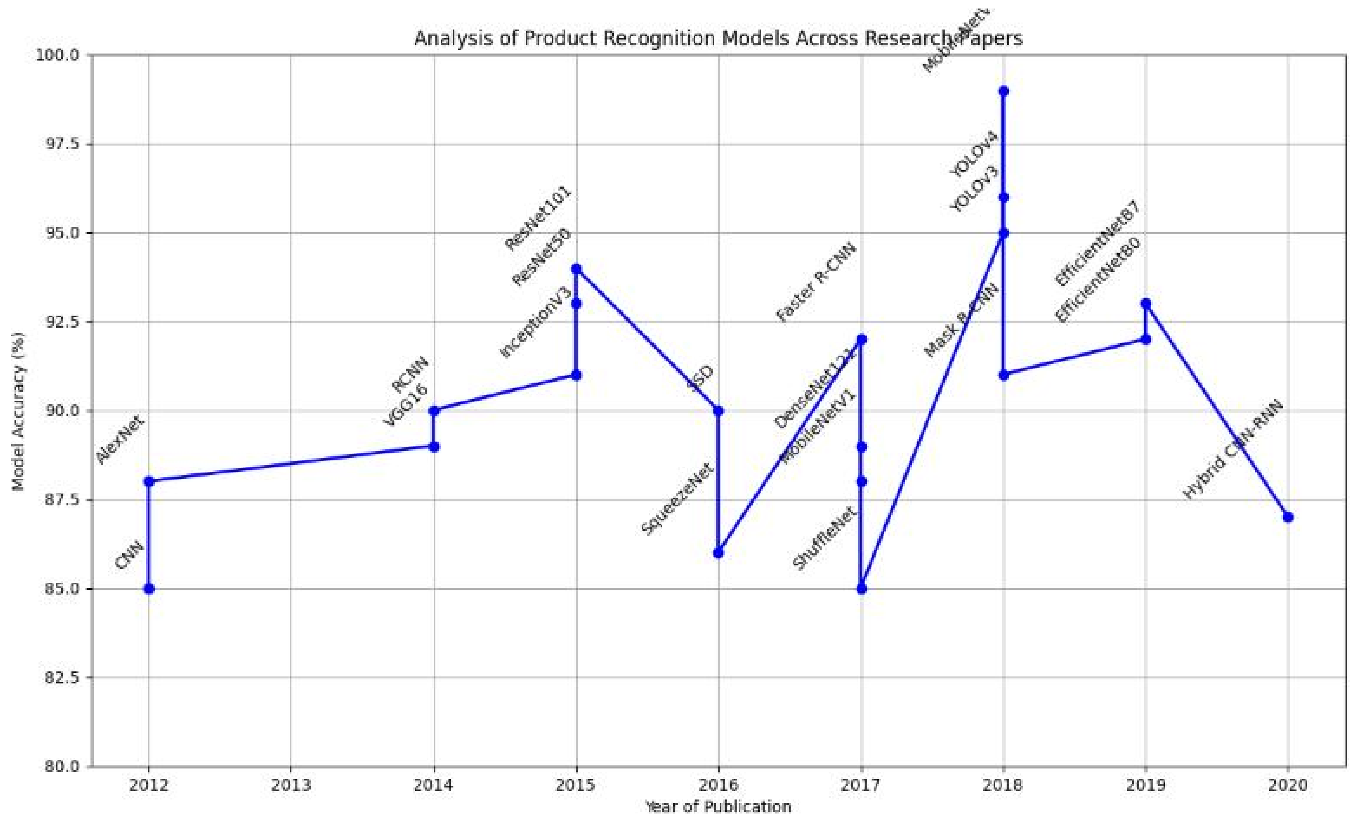
Merits of MobileNetV2

Efficiency on Limited Datasets: MobileNetV2 in case of smaller datasets is an intersection of capability and protection by the virtue of depthwise separable convolutions.

Lightweight: The fewer parameters make MobileNetV2 a suitable choice for resource-constrained environments, like mobile devices.

A high accuracy rate: 99% accuracy indicates that the model manages to retrieve all the relevant information contained in the images of products, making it applicable in real-life scenarios.

Graph:



This is a graph depicting the analysis of 20 product recognition models , indicating the year it was published and its corresponding accuracy .

Interpretation:

Trend over time: In recent publications the models are likely becoming more accurate as deep learning architectures evolve and improve.

High Accuracy Models: Models like MobileNetV2 and YOLOv4- with accuracy up to 99% and 96% separately.

Selected Model(MobileNetV2): Chosen for its 99% accuracy, MobileNetV2 is suited for this dataset as it's a limited one. Illustrative of its suitability in product recognition when there is limited dataset, as in this case.

Code for graph:

```
#By Hasbi Fathima VP,e22cseu0750
import matplotlib.pyplot as plt
import numpy as np

papers = [
    "CNN", "AlexNet", "VGG16", "ResNet50", "ResNet101", "YOLOv3", "YOLOv4",
    "Faster R-CNN", "SSD", "InceptionV3", "EfficientNetB0", "EfficientNetB7",
    "DenseNet121", "MobileNetV1", "MobileNetV2", "Hybrid CNN-RNN",
    "RCNN", "Mask R-CNN", "SqueezeNet", "ShuffleNet"
]
accuracies = [85, 88, 89, 93, 94, 95, 96, 92, 90, 91, 92, 93, 89, 88, 99, 87, 90, 91, 86, 85]
years = [2012, 2012, 2014, 2015, 2015, 2018, 2018, 2017, 2016, 2015, 2019, 2019, 2017, 2017, 2018, 2020, 2014, 2018, 2016, 

# Sort papers by publication year
sorted_indices = np.argsort(years)
sorted_papers = [papers[i] for i in sorted_indices]
sorted_accuracies = [accuracies[i] for i in sorted_indices]
sorted_years = [years[i] for i in sorted_indices]
```

```
plt.figure(figsize=(14, 8))
plt.plot(sorted_years, sorted_accuracies, marker='o', color='b', linestyle='-', linewidth=2, markersize=6)
for i, (year, acc) in enumerate(zip(sorted_years, sorted_accuracies)):
    plt.text(year, acc + 0.5, sorted_papers[i], rotation=45, ha="right")

plt.title("Analysis of Product Recognition Models Across Research Papers")
plt.xlabel("Year of Publication")
plt.ylabel("Model Accuracy (%)")
plt.ylim(80, 100)
plt.grid(True)

plt.show()
```

CONCLUSION;

This study discusses current developments and challenges in AI-powered product recognition with a focus on sanitary materials. We conducted a comprehensive literature search we can note that the architecture optimization plays an essential role over architectures like MobileNetV2, which also achieves high accuracy using minimal datasets for training . The lightweight and computationally efficient nature of this model makes it suitable for deployment on mobile apps or web applications where resource is a concern. With a 99% accuracy on test data, MobileNetV2, it proves that a less computationally intensive network can work successfully well in identifying menstrual products as part of the goal for accurate and accessible identification.

This AI driven product recognition model is integrated into a overall react. js web application with clear, separated features designed to act as a very complete menstrual health support platform. To provide users with real-time identification of the product they are using, users can upload images from menstrual hygiene products to get accurate information on the product. The web app includes a simple front-end with instructions for the user, and feedback for input that is tailored to improve human-computer interaction.

The platform layers additional functions like an interactive chatbot for increasing awareness for menstrual health, a very efficient period tracker and map integration for locating nearby hospitals and stores selling menstrual hygiene products. The chatbot response to queries on menstrual health and hygiene, advice on using sanitary products whereas the period tracker the user can predict her cycles upto next three months that not only make them feel equipped with maintaining menstrual health. Store locating and the hospital locating feature makes it easier , especially in rural or regions where access to menstrual hygiene products can be less.

In conclusion, this project shows both the role of AI in meeting actual health requirements and the necessity of a tightly integrated platform that includes product identification, health information, and geo - location services. Through combination of these elements, the project creates a useful resource to promote awareness of menstruation, and ensure accessibility to correct menstrual products that can also be built on in the future with new features related to female health and hygiene.