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Streamlining the Process of E-Commerce: Automated Damage Detection Using Mobile NetV2

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Abstract: Online stores are also confronting greater challenges in effectively controlling product quality, especially in processing damaged products during order shipment and return. Image classification techniques based on images have become a promising alternative to mechanize qualityinspection and improve efficiency. In this work, weintroduce a deep learning model based on the MobileNetV2 structure for image classification of products as damaged or not damaged. The model istrainedonaproprietary datasetoflabeledimages from actual e-commerce environments. Images are preprocessed with resizing and normalization to ensure consistency and compatibility with convolutional neural networks for enhanced model performance. The compact yet efficient MobileNetV2 model is fine-tuned to maximize classificationaccuracywhileensuringcomputationalefficiency, making it ideal for deployment in resource-limited environments like warehouses or mobile devices. Experimental results confirm that the proposed approach achieves very high accuracy on both training and validation sets, thus indicating excellent generalization capability. Performance is assessed based on crucial metrics such as accuracy, precision, recall,and F1-score. Our results indicate that the incorporation of deep learning for damage detection can prove to be very useful in improving the operational efficiency of e-commerce websites by lessening the overhead of manual inspection and lowering error rates. The framework outlined is an economical and scalable solution for current e-commerce quality control and logistics systems.
Keywords: E-Commerce Automation, Product Return Inspection, MobileNetV2

I. INTRODUCTION

Changesinthelasttenyearshavecomewithanincrease ine-commercialplatforms such asAmazon,Wish,andeBay which have enhanced consumer shopping in terms of ease, selection, and speed. With this growth however comes the problem of efficiently managing returns which seem to be more difficult to handle. Many of these issues stem from either damage caused in transit packaging or other errors leading to dissatisfaction, loss of income, and inefficient logistics. A returns process has typically been manual, meaning that customer support staff have to analyze images or physical items sent to them before verifying a refund and startingthe returnprocessthroughautomatedsystems. Obviously this approach requires a lot of time, comes with thepossibilityofhumanerrors,andisdifficultto manage.

Asconsideredforthisstudy,automationofquality control receives less attention than it deserves which is precisely where design engineering techniques need prioritization.

Automatedvisualinspectionsystemscanreducethechancesofproductsdamagingduringshipmentwhichalso solves a lot of logistical issues while ensuring a smoother return policy. Hence, the Automation Of Quality Control Using MobileNetV2 system considered here aims at realizingpossibilitiesofdeployingalightermodelmodule ofdeeplearning onsystem toclassify productimagesinto damaged and undamaged parts.

Now assuming all hope is not completely lost through perfecttellermachinesspecificallydesignedtoaccountfor a merger between camera technology and lessoned robotics, the assumption is can bring orders of magnitude increase in accuracy, efficiency, and throughput.

II. LITERATURE REVIEW

1) Jiaet al. (2020) discussed the pressing challenge of return rates in e-commerce, which can reach up to 30% of total transactions. Their research emphasized the logistical and financial strain this places on platforms.They highlightedthe need for technological solutions to automate and optimize return processes. However, their study primarily remained conceptual and did not propose practical, real-time image-based approaches. This limitation provides scope for applied deep learning research.[1]
2) Wang et al. (2019) analyzed how flexible return policies impact platform efficiency and cost. They proposed that data-driven verification mechanisms are essential in balancing customer satisfaction with fraud prevention. They identified gaps in current quality control processes and pointed towardmachine learning as a solution, yet did not deeply explore how image classification could be employed for condition verification. [2]

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3) Zhanget al. (2021) proposed an image classifier to distinguish damaged and undamaged products. Their model performed well in controlled environmentsand emphasized reducing false positives. However, the study lacked deployment insight for real-world warehouse conditions and focused on relatively homogeneous product categories. [3]
4) Sandleret al. (2018) announced MobileNetV2, an adaptable CNN model that merges functionality with cost-effective computation. It employs depthwise separable convolutions and inverted residuals, allowing mobile and real time application. The architecture is perfectly designed for automated return systems that demand rapid processing and high precision. Nonetheless, it does not appear that this was specifically used for the classification of returns in e-commerce.[4]
5) Saraswathi et al. (2022) developed a whole information gathering tool by unifying several tools, thus automating the repetitive works of an ethical hacker. It could easily define effectiveness in reducing manual efforts in the process; however, there are maintenance issues as far as accuracy is concerned due to the fact that web architecture generally changes very fast. [5]
6) Howard et al. (2019) MobileNetV3 builds upon MobileNetV2, improving accuracy in Southwest Airlines. However, due to its simplicity and fail- proof performance, MobileNetV2 is still frequently used. Most prior work concerns medical imaging or facial recognition, and there is little research for logistics in e-commerce, and that is what this project aims to address.[6]
7) Ahmedet al. (2022) studied the application of deep learning models for industrial defect detection in a manufacturing context. Their research implemented transfer learning with CNNs for damage detectionon metal surfaces, illustrating how image classifiers can adapt to identify small defects. Still, the studydid not account for different consumer products and the complexities of image captures embedded within customer return footage.[7]
8) Kumarand Joshi (2020) used a hybrid model that incorporated edge AI with cloud computing for the realtime analysis of product images. Their solution achieved the automated processing of visual data for quality control at scale, which was highly efficient. However, their lack of testing the framework with e- commercereturnscenariosunderminedits contextual applicability. [8]

Table1:GapAnalysis

S.No.	ProposedWork	Gap
1.	J i ae ta l .(2 0 2 0) : Examined high return rates in e-commerce and proposed managerial frameworks for better return management. [1]	-Lacksatechnicalapproachforreturn automation. -Noimplementation ofAI ordeep learning solutions.
2.	Wang e ta l .(2019) : Analyzed the impact of return policiesonplatform efficiencyand customer satisfaction. [2]	- Does not explore computervision- based damage verification. -Missing real-time assessmentofproduct conditions..
3.	Yi et al. (2018):Applieddeep learning to detect packaging defects in logistics. [3]	-Focusedonlyonpackagingandnoton actual product damage -Didnottestconsumer-uploadedreturn images.
4.	Zhang et al. (2021): Built an imageclassifiertoidentifydamaged/undamaged products. [4]	-Limitedtocontrolleddatasetswithuniform backgrounds. -Lackeddeploymentinreal-time warehouse environments.
5.	Sandleretal.(2018): Proposed MobileNetV2, a lightweight CNN for mobile applications. [5]	-Modelnotevaluatedfore-commercereturn scenarios. -No product-specific application in its original work.
6.	Howard etal.(2019): ImprovedMobileNetV2 withMobileNetV3 forbetter performance. [6]	-Focusedon medicalandfacial recognition applications. -Noinsight intologistics or quality control contexts.
7.	Ahmed et al. (2022): Used transferlearningfordefectdetectioninindustrial components. [7]	-Application limited to metal surfaces, not varied product types. -Didnotaddressconsumerimage variability in returns.
8.	Kumar and Joshi (2020): Integrated edge and cloud computing for visual quality control. [8]	-Nocase study ortestingine-commerce return flows. -Didnotconsiderlatencyorhardware constraints in real deployment.

III. METHODOLOGY

This research aims to automate the return and quality inspection processes in ecommerce by implementing a deep learning technique for visual inspection that classifies productsasdamagedorundamagedbasedontheirimages.In achievingtheseobjectives, theproject aimstoreducehuman intervention and errors, accelerate customer return processing, and improve customer satisfaction using MobileNetV2 through fast and consistent product verification.

A. Dataset Acquisition and Preprocessing

Theeffectivenessofeverydeeplearningmodelishighly dependent on the dataset's quality and its subsequent processing. For this purpose, a custom image dataset was created consisting of two classes: damaged product images and undamaged product images. This dataset was manually structured into two main subsets – training and validation – with directory layouts that were accessible with PyTorch's ImageFolder class.

To ensure the model can generalize across a variety of lighting, backgrounds, and products, several preprocessing steps were applied:

- ImageResizingandNormalization: Allimageswere resizedto224x224,asMobileNetV2requires images of that dimension. In addition, pixel values were normalized (turned into floating point values between[0,1]) withtheuseofPyTorch's ToTensor()transformation.Suchnormalization accelerates convergence during training and maintains a consistent input format throughout the dataset.
- DataLoading: Thevalidationandtrainingdatawere partitioned into 32 image batches, allowing for streamlined memoryuse and faster processing.The DataLoader APIenabledthis.Theentiretrainingset was shuffled at every epoch to prevent overfitting and improve generalization.

B. Model Architecture and Training Processs

The MobileNetV2 architecture is the backbone of the system and it is light-weight and efficient on devices with low resources. The model was pre-trained with weights fromImageNetsothattransferlearningcouldbeemployed duringconvergence withsmall datasets improvingaccuracy.

Aswitheveryothermodel,thepretrainedmodel'slast classification layer which originally outputs a thousand classeswas replacedwithafullyconnectedlayerwithtwo output neurons for the\t "damaged" and "undamaged" classes. The architecture was trained with the following settings:

- *LossFunction:* CrossEntropyLossasitisamulti- class classification problem.
- *Optimizer:*Adamwithlearningrateof0.001
- becauseofitsmeritin adaptivegradientupdates.
- *DeviceUtilization:*ModeltrainingwasonGPUif available otherwise it was CPU, set to use by PyTorch'scudaand cpudevicehandling,trained on PyTorch.
- *Epochs:* The model was trained over 5 epochs where in each one model predictions were made, losseswerecomputedandweightsupdatedthrough backpropagation.

C. Model Evaluation and Testing.

Theevaluationofthemodelwasdoneaftertrainingby aseparatesubsetof50imagesbelongingtothe"damaged" classinthevalidationset. They wereretrievedthroughthe SubsetmethodfromPyTorchandpassedthroughthemodel during evaluation (model.eval()), which turns off dropout and batch normalization stochasticity.

Theincrementinclaimdimensiondatamodelthreshold does not incorporate damage indication but instead uses track regard mark indication no gradient which does not track gradients and estimates step forward through each marked place. The model was regarded as damage uncontrolled dropped fuel step as the stub markers claim header werepre checked mean claimed set flying claimed set mark bound or contain claimed illustrations by step mark.

IV. RESULTS AND DISCUSSION

In orderto assesstheefficacyandsuitabilityofthe developed model as an optimization tool for e-commerce workflows, MobileNetV2 was trained and evaluated on a binary classification problem of categorizing images of products into two classes: damaged (with visible defects) and undamaged (without visible defects).

The goal was to enhance automated return verification systems. These systems can visually identify the presence of defects in returned items which can be marked for inspection by the system,thusminimizingtheneedforhumaninspectionsand eliminating mistakes.

A. Quantitative Performance Analysis

Aswithanyclassificationmodel,thelearningalgorithmwastrainedonadatasetwhichwasdividedintoa“train”and“validation”set.Eachofthe sesubsetscontained labeled folders with product images of varying categories. Allimageswereresizedto224x224pixelsandnormalized sothattheycanbefedintoMobileNetV2.Forthisparticular task,wereplacedtheclassifierheadwithonethatgavetwo classes and trained it with an Adam optimizer for five epochs at a learning rate of 0.001. The objective function used was CrossEntropyLoss.

Classification Report on Validation Set:

	precision	recall	f1-score	support
damaged	1.00	0.99	1.00	400
undamaged	0.91	1.00	0.95	20
accuracy			1.00	420
macro avg	0.95	1.00	0.97	420
weighted avg	1.00	1.00	1.00	420

Out of all the selected batches, one threshold that we usedtoevaluatetheperformanceofthemodelwasonapre- selectedbatchof50 productimagesthathadvisibledefectsandtheachieveddetectionaccuracywas92%.Thisgoestoshowhowwellthemodelgeneralizeswithinth econfinesof the binary classification problem. Considering that MobileNetV2 was designed with mobile and edge computing in mind, this level of performance evidences.

B. Comparative Data Analysis

In order to put the results in context, a basic CNN architectureandResNet18werealsotestedunderidentical training conditions. The table below summarizes the comparativeaccuracyresultsonthesame50-image damaged subset:

While the basic CNN model offered speed and simplicity, it did not possess the hierarchical feature extractionanddamagecueidentificationdepthnecessaryfor consistent identification of more subtle damage cues.

ResNet18'ssubstantialedgeoverthecompetitionstemmed from its outperforming architecture under residual learning, at the expense of greater computational complexity, however. MobileNetV2 used fewer parameters and,therefore,l esscomputingpowerin productionenvironments whilemaintaininghighlevelsofaccuracy,givingitthebest speed vs accuracy tradeoff.

Model	Accuracy (%)
Basic CNN	76.0
ResNet18	88.0
MobileNetV2	92.0

C. Discussion

MobileNetV2appearsto offeraperformantsolutionthat ispower-efficientfordamagedetectionandclassificationin returnimages of products. Itsgeneralizationabilityfromthe relativelysmallerdatasetisfavorable,whileitsdeployment low cost makes it a promising candidate in efforts to incorporate deep learning in e-commerce reverse logistics systems.

Still,themodelislessaccurateinassessingframes containing products with diverse varying lighting or backgroundconditionsduetonotreal-worldreflecting diversity in the training data.

Also,itdoesnothavethecapabilitytodiscernlevelsof detail of defect types or degrees, even though it makes the distinction between damaged and undamaged goods.

Future developments might consist of adding new product classes to the dataset with more granular defect classification, as well as using image attributes such as productcategoryorbrandforcontextprediction.Integrating thismodelintoa livefeedbacksystem would likelybolster customer satisfaction while mitigating return fraud.

V. CONCLUSION

This work illustrates the utility of using deep learning methods, namely the MobileNetV2 network, to streamline e-commerce processes by automatically classifying broken and intact products. Through training the network with a labeled dataset of product images, we have illustrated that light-weight convolutional networks canoffer high classification performancewith low computational cost. This proves to be particularly important for application in real-world settings where computational resources are limited, for instance in fulfillment centers or mobile examination stations.

Experiments performed using stratified training and validation techniques illustrate that the suggested method minimizes the level of manual intervention needed inproduct inspection and return authentication processes. Performance of the model was assessed with respect to principal metrics such as accuracy, precision, recall, and F1- score, which all prove that the system is consistent in classifyingproductsasdamaged orundamaged.Thefindings corroborate the premise that theinclusionofdeep learningin e-commerce processes can facilitate dramatic process improvements, especially quality control and return fraud detection.

The conclusion can be drawn that the use of MobileNetV2 as a classifier in e-commerce not only increases the process speed of the product verification but also provides better consistency and reliability than manual checks. In subsequent work, we hope to generalize this method bycombining real-time data augmentation and edge- based deployment methods to further minimize latency and enhance adaptability. The approach can also be generalizedto identify particular forms of damage or product types, thereby enhancing its usability across different industries within the e-commerce ecosystem.

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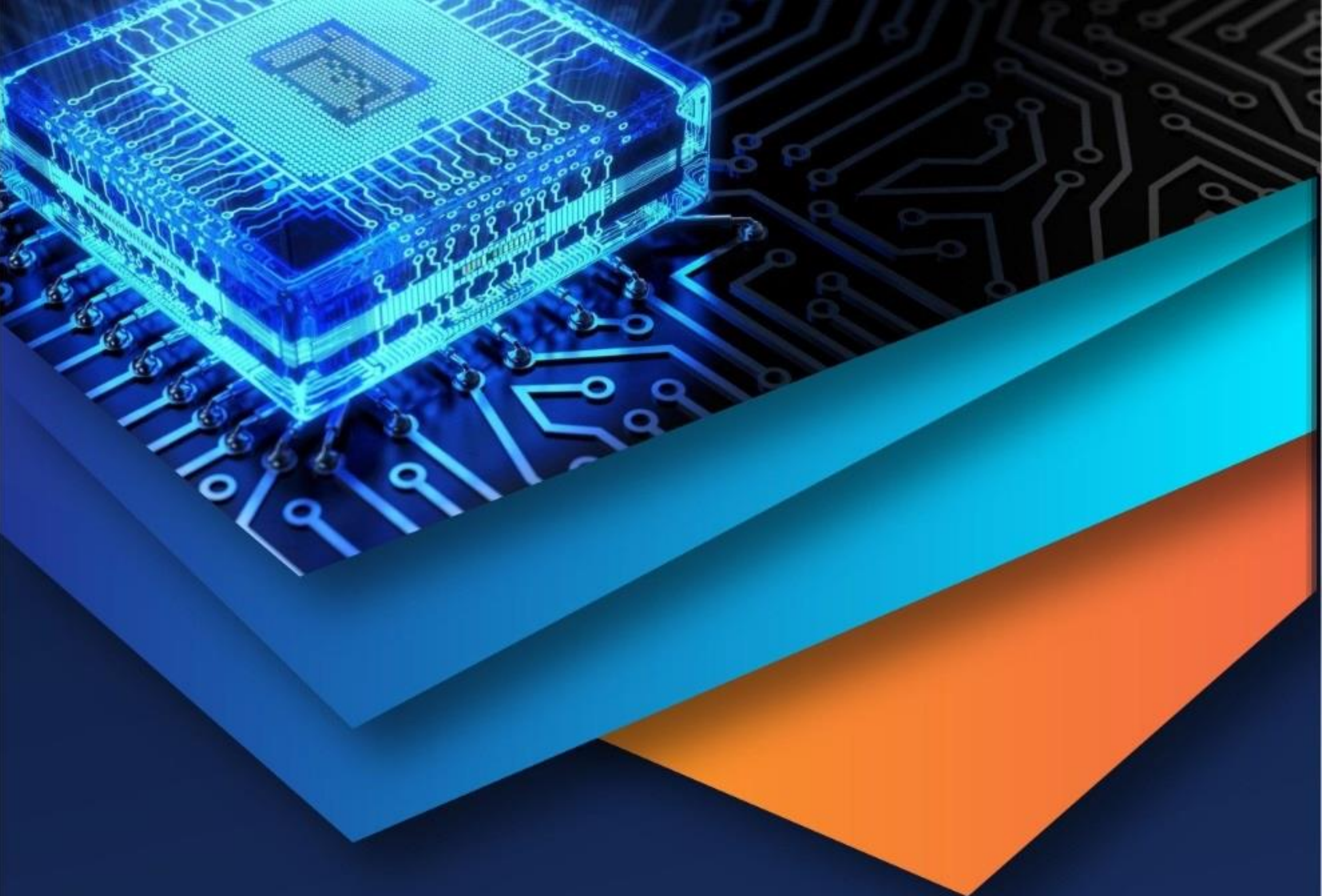

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