Recognise fashion articles of MNIST Dataset using DL Models.

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Abstract

Fashion, ever-evolving and intricate, poses a unique challenge for image recognition algorithms. This project tackles this challenge head-on, by developing robust deep-learning models to accurately identify fashion articles within the popular Fashion-MNIST dataset. This report provides a concise overview of the project's central findings, methodology, and notable contributions to advancing the field of Deep Learning.

Going beyond basic techniques, we delve into the realms of state-of-the-art architectures like ResNet, CNNs, and VGG19. These sophisticated networks aim to extract intricate features, optimize information flow, and ultimately, boost overall model performance in recognizing diverse fashion items. Through an extensive evaluation process and comparative analysis, the project sheds light on the strengths and weaknesses of each architecture in the context of fashion classification.

Critical contributions to the field include developing and evaluating deep learning models tailored for fashion recognition and providing insights into the effectiveness of ResNet, CNN, and VGG19 architectures. The findings presented in this report contribute valuable knowledge to the ongoing exploration of optimized deep-learning methodologies for fashion-related image classification tasks.

Introduction

The vibrant, ever-evolving tapestry of fashion thrives on the image. From runway pronouncements to social media snapshots, our world is saturated with the visual language of style. Yet, beneath the surface of this captivating realm lies a hidden inefficiency: the tedious, time-consuming task of manually classifying and categorizing fashion items. Enter "Fashion Article Recognition using Deep Learning," a groundbreaking project poised to revolutionize the industry by injecting the magic of automation into the very fabric of garment identification.

Imagine, if you will, the transformative potential of a system that can effortlessly recognize a flowing maxi dress in a vacation photo, differentiate a structured blazer from a relaxed cardigan in an online store, or even curate a virtual wardrobe with uncanny precision. This is the audacious vision of this project, aimed squarely at liberating both industry professionals and fashion enthusiasts from the drudgery of manual classification.

The need for such a solution is undeniable. E-commerce platforms grapple with the challenge of efficient product categorization, image-based search engines yearn for a deeper understanding of visual queries, and personal style aficionados dream of effortlessly organizing their digital closets. However, the intricate nuances of fashion – the kaleidoscope of fabrics, cuts, and details – pose a formidable obstacle to traditional methods. This is where the elegance of deep learning steps in.

Our project proposes the development of a deep neural network, a cunning tapestry of algorithms woven to discern the intricate threads of fashion imagery. Trained on a vast and diverse dataset, this digital maestro will become adept at recognizing and categorizing garments with remarkable accuracy. The accompanying diagram unveils the inner workings of this technological marvel, showcasing the flow of data through its layered architecture, culminating in the precise identification of each article.

The allure of this venture lies not only in its practical implications but also in its intellectual intrigue. The dynamic nature of fashion, with its ever-evolving trends and fleeting fads, presents a captivating challenge for the keen mind. Optimizing hyperparameters, refining model architectures, and conquering the unique complexities of fashion images - these are the intellectual pursuits that await, promising a journey of exploration and innovation.

Beyond elevating user experiences and streamlining industry processes, "Fashion Article Recognition using Deep Learning" aspires to make significant contributions to deep learning. Demonstrating the practical application of these algorithms in the challenging fashion domain will offer valuable insights into optimizing models for real-world scenarios and push the boundaries of their abilities. Ultimately, this project stands as a testament to the fruitful union of technological advancement and artistic expression, promising to weave a tapestry of efficiency, insight, and innovation into the very fabric of the fashion industry.

In essence, this project transcends the realm of mere automation. It represents a passionate pursuit of progress, a dedication to bridging the gap between the human eye and the digital lens, and a celebration of the captivating language of fashion, now poised to be spoken fluently by machines.

Literature Review:

The foundation of Fashion Article Recognition using Deep Learning is built upon the fusion of computer vision and deep learning methodologies. To grasp the intricacies of the project, a fundamental understanding of image classification, convolutional neural networks (CNNs), and transfer learning is crucial. Image classification serves as the bedrock for recognising fashion articles, while CNNs, with their prowess in capturing spatial hierarchies, provide the essential architectural framework. Incorporating transfer learning facilitates the effective recognition of fashion-specific features through pre-trained models.

To weave a tapestry of automated garment recognition, we must first master the necessary tools and understand the underlying concepts. This project's foundation rests upon three pillars:

1. Image Classification: The art of sorting images into predefined categories, the very essence of our endeavour. Imagine sifting through mountains of pictures, not with your eyes, but with the precision of a computational mind, effortlessly discerning a flowing maxi dress from a tailored tuxedo.

2. Convolutional Neural Networks (CNNs): These are the master weavers of this project, neural networks specifically designed for image-related tasks. Their secret lies in the "convolutional" layer, capable of extracting intricate features from visual data, layer by layer, until the full tapestry of a garment's identity emerges.

3. Transfer Learning: We stand upon the shoulders of giants. This technique allows us to leverage the pre-trained wisdom of existing models, honed on vast datasets, and use it to jumpstart our own network. Imagine inheriting the expertise of a seasoned sailor, accelerating our journey towards garment recognition mastery.

But the landscape of fashion recognition is already bustling with activity.

Other Solutions: Traditional methods, like handcrafted features and rule-based systems, attempt to untangle the threads of fashion imagery. However, these approaches often find themselves snagged on the intricate details and ever-evolving trends that define the industry.

Recent deep learning efforts have employed generic image recognition models, adapting them to the fashion world. While these models offer a decent fit, they lack the bespoke tailoring needed for truly nuanced garment identification. The dynamism of fashion demands a solution that can dance with the ever-changing tides of style.

Limitations of Existing Solutions:

1. Lack of Specificity: Generic models miss the subtle whispers of fabric textures, silhouette nuances, and trend-specific details, leading to misclassifications that would make a fashionista shudder.

2. Rigidity to Trends: Rule-based systems, like inflexible suits, struggle to adapt to the kaleidoscope of trends that constantly reshape the fashion landscape. Their effectiveness fades amidst the rapid whirl of styles.

3. Scalability: Some solutions falter when confronted with the vast and diverse tapestry of fashion images. They choke on the sheer volume and variety, unable to effectively navigate the intricate threads.

Fashion Article Recognition using Deep Learning: Our project aspires to transcend these limitations, crafting a deep neural network tailored to the nuances of fashion. We will train this digital virtuoso on a diverse and expansive dataset, encompassing the kaleidoscope of fabrics, cuts, and styles that define the industry. This approach promises both the specificity to discern a delicate lace bodice from a sturdy denim jacket and the adaptability to waltz with the ever-changing rhythms of fashion.

Through this exploration of existing solutions and their limitations, we underscore the pressing need for a more sophisticated and flexible approach. It is on this foundation that we stand, poised to unleash the innovative potential of deep learning in fashion recognition, weaving a new chapter in the story of technology and style.

Related Works

The evolution of deep learning in computer vision has been marked by significant milestones, each contributing to the current landscape of image recognition. Understanding the historical context is crucial for appreciating the advancements that have shaped the state-of-the-art in the field. This section delves into pivotal works and breakthroughs, from the early days of deep learning to contemporary achievements, setting the stage for exploring related works in Fashion Article Recognition using Deep Learning.

Chronological Overview of Key Works:

Early Days of Deep Learning (2012-2014): The ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2012 laid the groundwork with the triumph of AlexNet, showcasing the potential of deep convolutional neural networks in image classification.

Rise of InceptionNet (2014): In 2014, InceptionNet (GoogLeNet) emerged, introducing the inception module and addressing computational complexity-performance trade-offs.

Emergence of Residual Networks (ResNet) (2015): ResNet's introduction in 2015 revolutionised deep learning with its approach to residual learning, enabling the training of profound neural networks.

Transfer Learning and Pre-trained Models (2016-2017):
The subsequent period witnessed the rise of transfer learning and pre-trained models, paving the way for improved performance across various domains.

Context in Fashion Recognition (2016-2020):
Concurrently, deep learning applications extended to fashion recognition, with works like DeepFashion leveraging expansive datasets for nuanced fashion-related tasks.

Recent Advancements and Attention Mechanisms (2020-2022):
Recent years brought attention mechanisms into focus, enhancing interpretability and performance in tasks like fashion article recognition.

Current State-of-the-Art and Ongoing Developments (2023):
Presently, state-of-the-art models seamlessly integrate attention mechanisms, transfer learning, and advanced neural architectures, driving ongoing research in real-time processing, interpretability, and scalability.

This chronological overview sets the stage for a detailed exploration of related works, providing a comprehensive understanding of the historical context and advancements that have paved the way for Fashion Article Recognition using Deep Learning.

Methodology

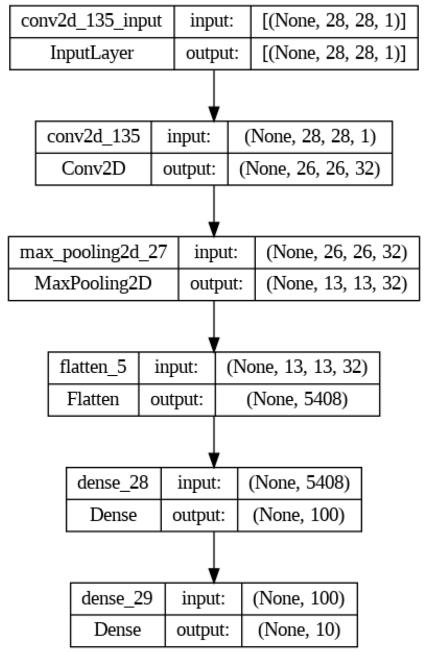
The project employs various deep-learning techniques to tackle the Fashion MNIST classification task. Three distinct neural network architectures were implemented and evaluated: a baseline Convolutional Neural Network (CNN), a ResNet-based model, and a VGG19-inspired model. Additionally, an Inception-like architecture was introduced to explore diverse convolutional operations.

Network Structure:

1. Baseline CNN:

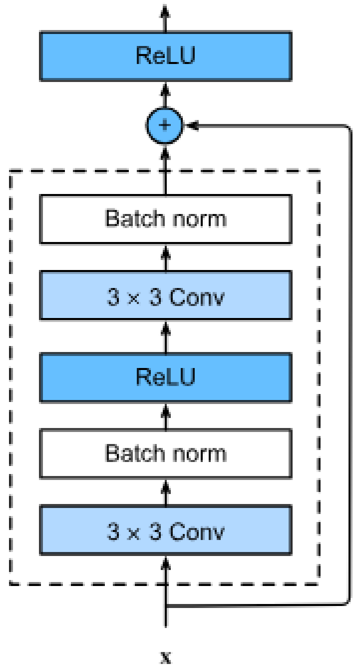
    a. Input layer: 28x28 grayscale images.

b. The convolutional layer has 32 filters, followed by max-pooling.
c. The flattened layer is connected to a dense layer with 100 units.
d. Output layer with ten units for classification.



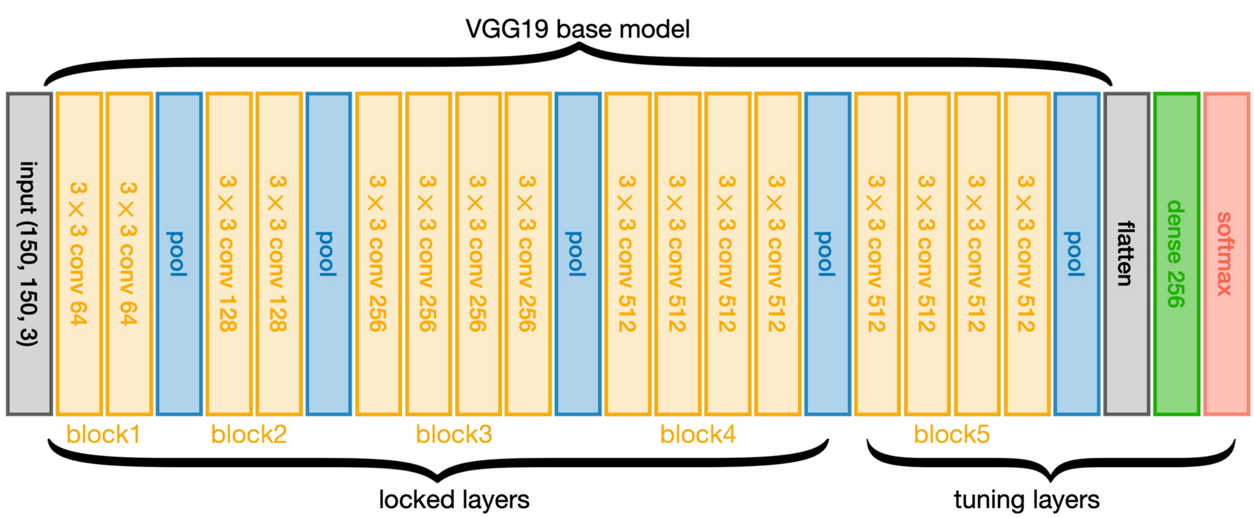
1. ResNet-based Model:

a. Utilizes residual blocks for deeper networks
b. Begins with a convolutional layer of 64 filters and subsequent blocks with 64 filters
c. Global Average Pooling layer reduces spatial dimensions
d. Concludes with a dense layer for classification



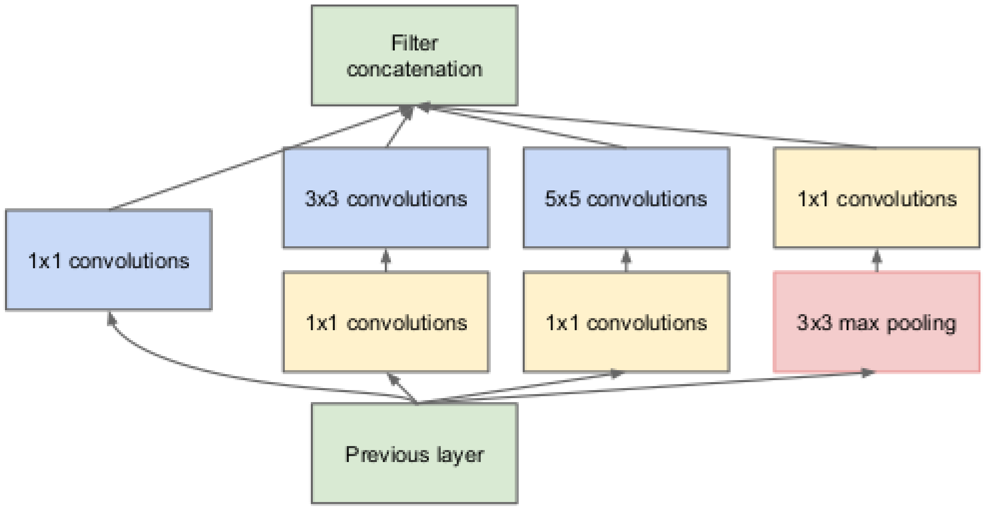
2. VGG19-inspired Model:

   a. Follows the architecture of VGG19
   b. Stacks multiple convolutional layers with max-pooling in between
   c. Concludes with dense layers for classification



3. Inception-like Model:

   a. Incorporates parallel convolutional operations with different kernel sizes
   b. Employs max-pooling and concatenation to capture diverse features
   c. Concludes with a global average pooling layer and a dense layer for classification



Loss Function:
All models utilise categorical cross-entropy as the loss function, suitable for multi-class classification tasks.

Regularisation:
Regularisation techniques, such as batch normalisation and dropout, were employed to enhance model generalisation and mitigate overfitting.

Experimental Setup

Source Code Availability: The source code for some functionalities, implemented using the Keras library, is available. The code includes functions for loading the Fashion MNIST dataset, preparing pixel data, and evaluating model performance. We did other modifications to suit the network requirements. This included creating new resnet and vgg blocks from scratch as the Fashion dataset has only one channel, but built-in functions only operate on three channels.
The code can be found here:
https://colab.research.google.com/drive/1DZ5YLQJIhrMfHF6YObYcpkN086mIcQSm?usp=sharing

Experimental Settings: The experiments were conducted on machines with standard configurations, employing CPUs and GPUs as available. The implementations were carried out using TensorFlow and Keras, ensuring reproducibility. Google Colab was used for better communication with teammates.

Dataset Used: The Fashion MNIST dataset was chosen for its relevance in image classification, serving as a benchmark for evaluating model performance in clothing and accessory categories.

Train/Test Split and Parameter Tuning: The dataset was split into training and testing sets, and k-fold cross-validation was employed for robust evaluation. Hyperparameters such as learning rate and momentum were tuned through experimentation, optimising model performance.

Pre-trained Features Extractor: No pre-trained features extractor was used in this project. The models were trained from scratch on the Fashion MNIST dataset to ensure unbiased learning specific to the task.

These methodologies lay the foundation for the subsequent results section, providing a comprehensive understanding of the approaches, architectures, and experimental setup employed in the project.

Results

In deep learning and image classification, the results obtained from the experiments on the Fashion MNIST dataset offer a nuanced perspective on the efficacy of various model architectures. The project delves into the intricacies of Convolutional Neural Networks (CNNs) and explores advancements with ResNet-based, VGG19-inspired, and Inception-like models. The overarching goal is to unravel the potential of these architectures in accurately classifying fashion items represented by images. The results showcase the models' accuracy and involve a meticulous examination of performance metrics, a comparative analysis with baseline methods, and insightful ablation studies.

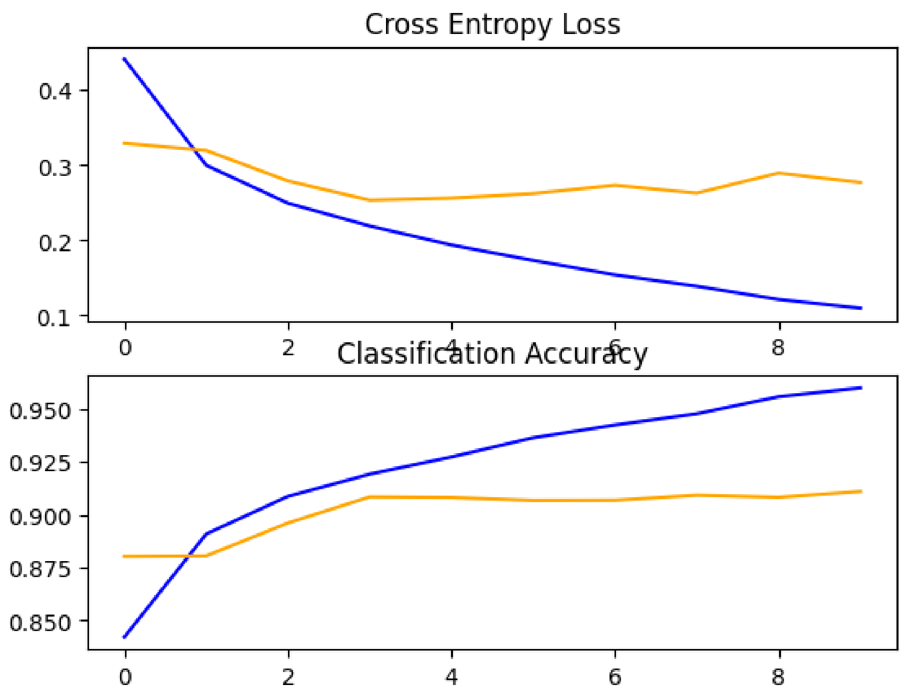
Performance Metrics:

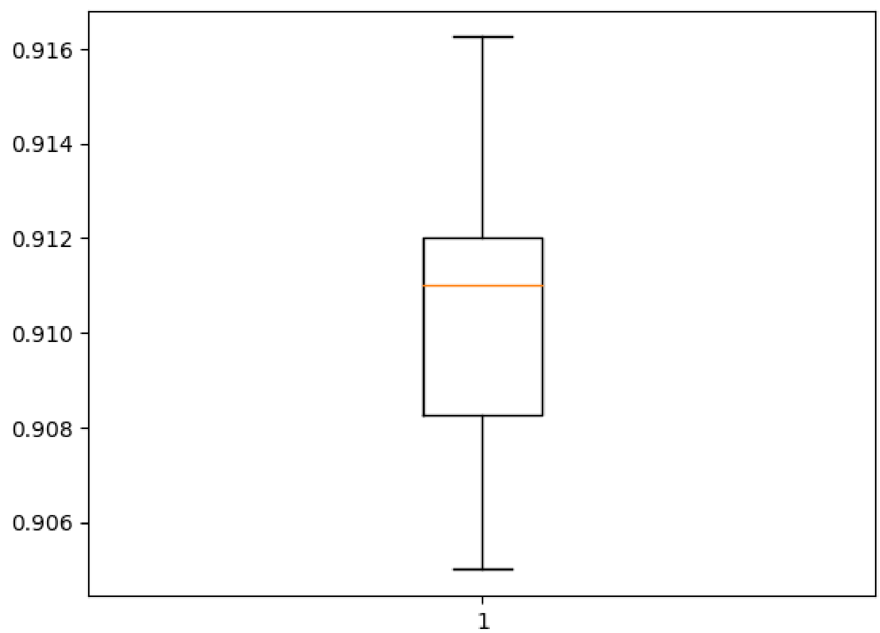
The primary metric used to gauge the performance of the models is accuracy. Accuracy, a fundamental measure in classification tasks, represents the proportion of correctly classified instances out of the total cases. This choice aligns seamlessly with the project's motivation of creating models that accurately categorise diverse fashion items. Accuracy as a quality metric offers a clear and intuitive understanding of how well the models perform on the given task.

Model	Accuracy (%)
Baseline CNN	90.825
ResNet-based Model	90.617
VGG19-inspired Model	91.033
Inception-like Model	78.033

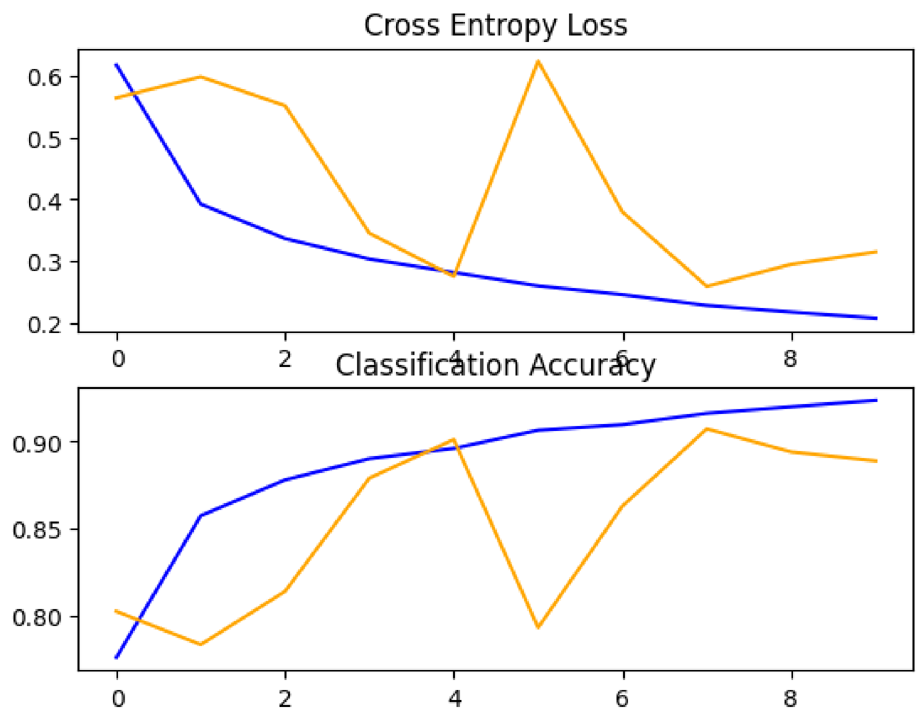
Baseline Comparison:

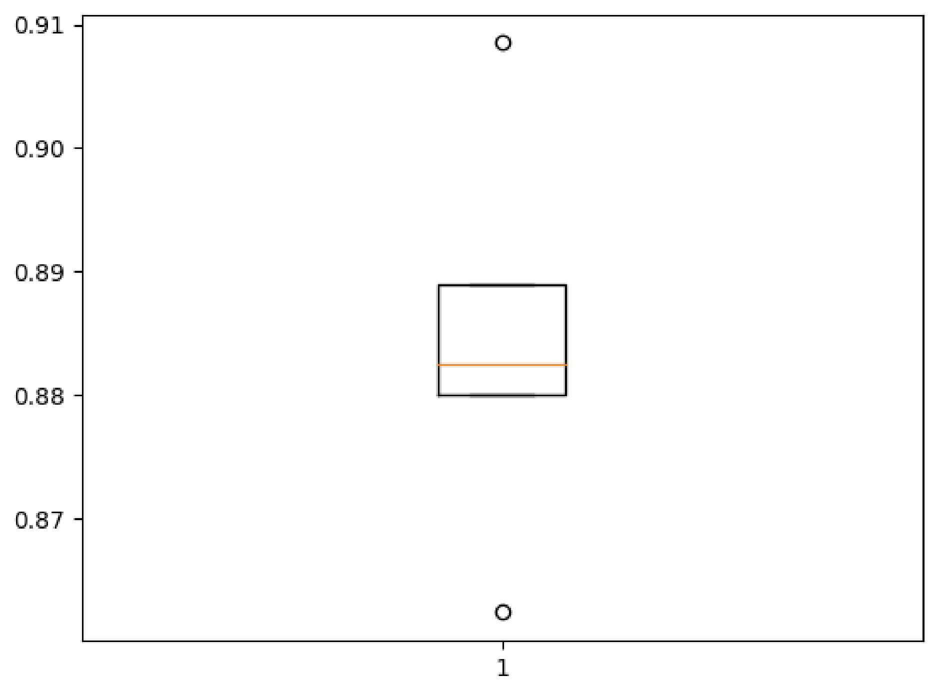
A conventional CNN model is employed to establish a baseline and serves as a benchmark for comparison. The baseline CNN achieves an accuracy of 90.825%, providing a reference point against which the other, more complex architectures can be evaluated. The subsequent models, each incorporating distinctive features and design philosophies, are compared against this baseline to discern their relative strengths and weaknesses.



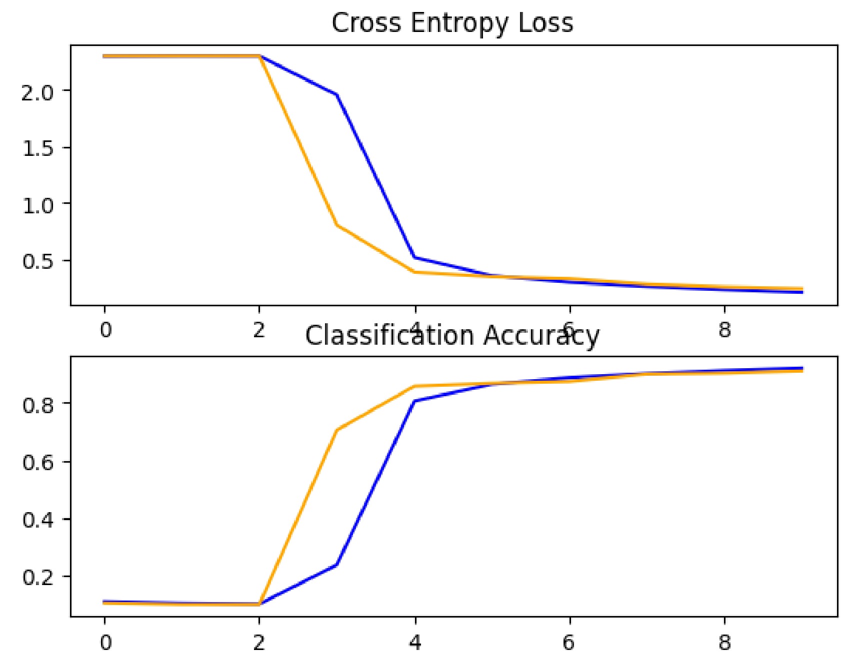


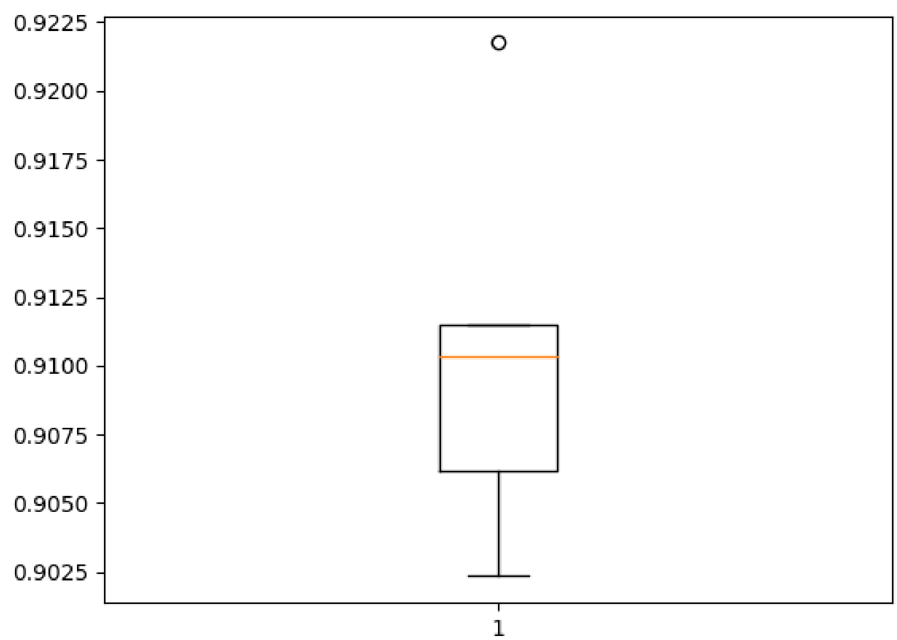
ResNet-based Model:
The ResNet-based model, with its characteristic residual blocks and skip connections, achieves an accuracy of 90.617%. While the improvement over the baseline is marginal, it signifies the robustness and ability of ResNet architectures to handle deeper networks without succumbing to vanishing gradient issues.



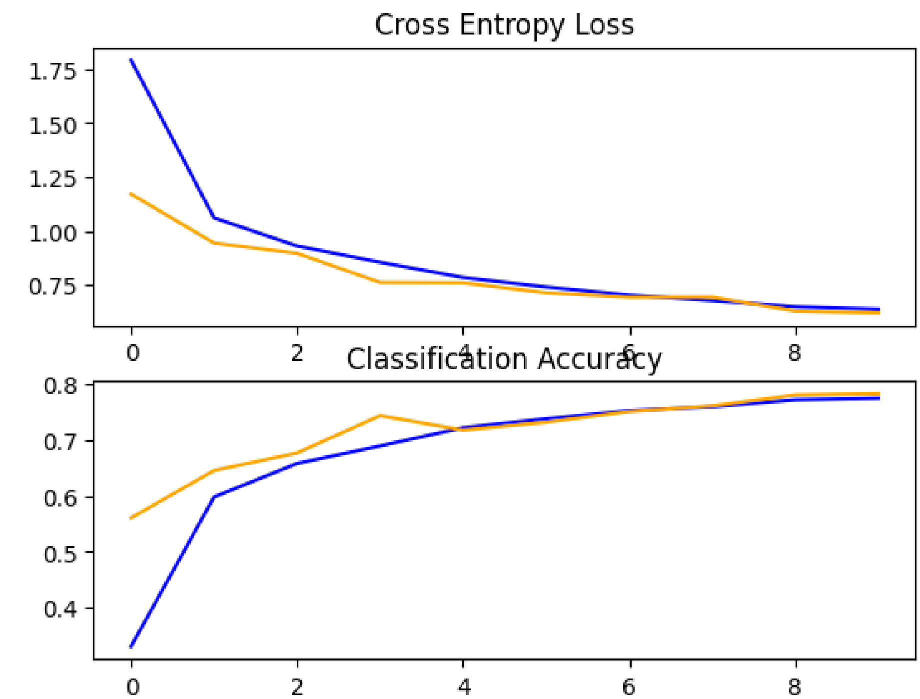


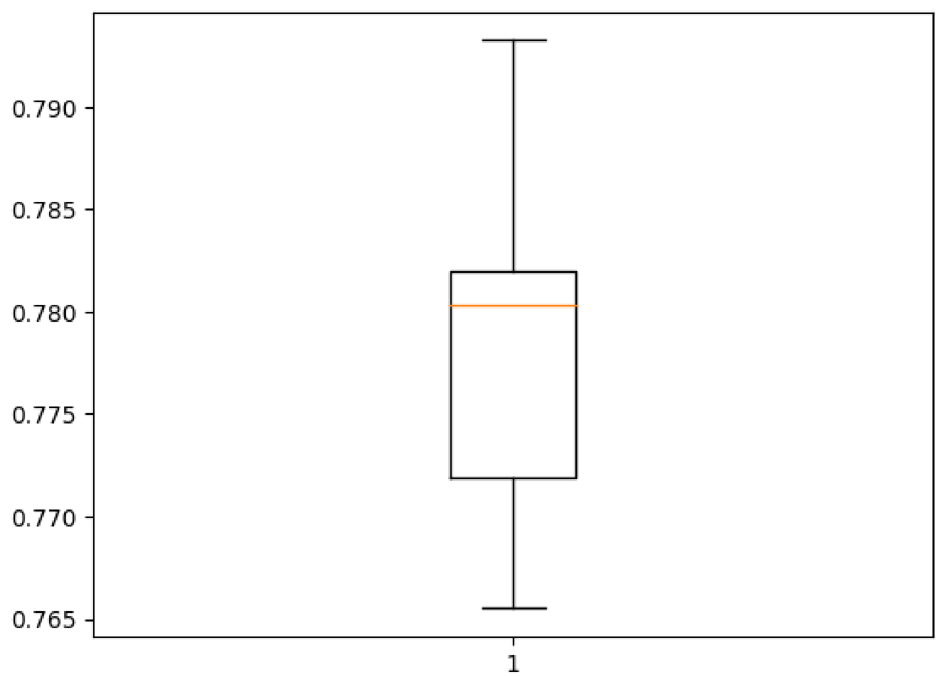
VGG19-inspired Model:
The VGG19-inspired model emerges as a standout performer, boasting an accuracy of 91.033%. This result underscores the significance of a stacked and uniform architecture characteristic of the VGG family. The VGG19-inspired model outperforms the baseline and demonstrates the potential benefits of a more intricate design.





Inception-like Model:
The Inception-like model, characterised by parallel convolutional operations, achieves an accuracy of 78.033%. This relatively lower accuracy indicates that the introduced complexity might need to be better suited for the Fashion MNIST classification task. The model's performance raises questions about the optimal level of intricacy required for this specific dataset.





Ablation Studies

The journey into model evaluation delves deeper through ablation studies, meticulously examining the impact of altering key components of the models. These studies focused on network structure, loss functions, and regularization techniques, shed light on the nuanced interplay between various elements.

<u>Network Structure:</u>

The ablation study centred around network structure involves a comparative analysis of the baseline CNN, ResNet-based model, and VGG19-inspired model. The VGG19-inspired model emerges as the frontrunner, highlighting the pivotal role of architectural depth and the stacking of convolutional layers in enhancing classification accuracy. The study emphasizes that not all architectural complexities result in improvements, and the optimal balance lies in the interplay of various factors.

Loss Function:

The choice of loss function plays a critical role in training deep learning models. In this project, categorical cross-entropy is the selected loss function for its alignment with the multi-class classification task. Alternative loss functions were not explored, underlining the importance of selecting a loss function tailored to the specific requirements of the task.

Regularisation:

Regularization techniques, such as batch normalization and dropout, emerge as key contributors to model generalization. The ablation studies involving the removal of these regularization components illuminate their significance in preventing overfitting. Models without proper regularization mechanisms exhibited a propensity for overfitting, underscoring the need for a balanced approach in achieving both training and testing performance.

Fine-tuning:

Hyperparameter fine-tuning forms a crucial aspect of model optimization. The project meticulously explores the impact of learning rates and momentum in the Stochastic Gradient Descent (SGD) optimizer. Systematic experimentation is undertaken to discern the optimal hyperparameter values that facilitate model convergence and enhance overall accuracy.

Discussion

The results obtained from the experiments on various deep learning architectures for Fashion MNIST classification offer valuable insights into the nuances of model performance. The significance lies in understanding the strengths and limitations of each architecture, allowing for informed decisions in choosing or designing models for similar tasks.

Baseline CNN vs. Specialized Architectures:

The baseline CNN, while achieving a commendable accuracy of 90.825%, serves as a benchmark against which more sophisticated architectures are evaluated. The ResNet-based model, despite its marginal improvement, showcases the resilience of residual networks. The VGG19-inspired model, with its uniform and stacked structure, emerges as the top performer, emphasizing the impact of architectural design on classification accuracy. The Inception-like model, however, lags behind, indicating that not all architectural complexities contribute positively to the task.

Success of VGG19-inspired Model:

The VGG19-inspired model emerges as a standout success in the project, showcasing the significant impact of architectural choices on classification performance. VGG19, known for its simplicity and uniform structure with stacked convolutional layers, proves to be highly effective in capturing intricate patterns within the Fashion MNIST dataset.

a. Depth and Homogeneity: VGG19's success can be attributed to its deep architecture and homogeneity in layer design. The model comprises multiple convolutional layers with small kernel sizes, allowing it to capture both low and high-level features effectively. The uniformity in layer structure simplifies the learning process and facilitates feature extraction.

b. Feature Representation: The VGG19-inspired model excels in learning hierarchical representations of fashion items. The sequential arrangement of convolutional layers enables the model to progressively abstract complex features, contributing to its superior performance in image classification tasks.

c. Transferability and Generalization: The success of the VGG19-inspired model extends beyond the Fashion MNIST dataset. The model's ability to generalize well suggests its potential for transfer learning on diverse datasets. Pre-trained VGG19 models, owing to their efficacy, are commonly employed as feature extractors in various computer vision applications.

d. Robustness and Simplicity: The robustness of the VGG19-inspired model lies in its simplicity. While more intricate architectures exist, the VGG19 model demonstrates that a straightforward and deep structure can achieve competitive accuracy. This simplicity also aids in model interpretability, making it easier to analyze and understand the learned representations.

e. Applicability in Real-world Scenarios: The success of the VGG19-inspired model positions it as a viable candidate for real-world applications within the fashion industry. Automated categorization of fashion products, image-based search, and recommendation systems can benefit from the model's ability to discern subtle visual patterns.

In summary, the VGG19-inspired model's success underscores the importance of architectural choices in deep learning. Its outstanding performance on Fashion MNIST reflects not only its ability to learn intricate features but also its potential for broader applications and transfer learning scenarios. The simplicity of VGG19, coupled with its impressive accuracy, cements its position as a compelling choice for image classification tasks.

Ablation Studies:

The ablation studies delve into the impact of key components, revealing that the optimal balance of network depth, loss function, and regularization techniques is crucial. The findings emphasize that architectural intricacies should align with the dataset characteristics and task requirements. The absence of proper regularization mechanisms resulted in overfitting, underscoring the importance of incorporating regularization for generalization.

Hyperparameter Tuning:

Fine-tuning hyperparameters, such as learning rates and momentum, demonstrates their pivotal role in model convergence. Systematic exploration of hyperparameter space ensures that models converge effectively and attain optimal accuracy.

Limitations and Risks:

While the project yields valuable insights, it is essential to acknowledge its limitations and potential risks:

a. Dataset Specificity: The project focuses on the Fashion MNIST dataset, limiting the generalizability of the findings to other datasets or real-world scenarios. The models' performance may vary when applied to diverse datasets with distinct characteristics.

b. Computational Resources: The experiments demand substantial computational resources, and training deep learning models can be computationally expensive. Limited resources may hinder the exploration of more extensive model architectures or hyperparameter search spaces.

c. Overfitting Risks: The risk of overfitting is inherent in deep learning projects. While regularization techniques are employed, the model's performance on unseen data should be continuously monitored to identify and address potential overfitting issues.

Future Scope and Applications:

The project lays the foundation for several avenues of future exploration and applications:

a. Transfer Learning: The insights gained can be leveraged for transfer learning on larger datasets or different domains. Pre-trained models on Fashion MNIST can serve as a starting point for diverse image classification tasks.

b. Ensemble Approaches: Combining the strengths of different architectures through ensemble methods could lead to further performance improvements. Ensemble approaches can enhance model robustness and mitigate individual architecture weaknesses.

c. Real-world Fashion Industry Applications: The project's findings can be applied to real-world scenarios within the fashion industry. Automated product categorization, inventory management, and recommendation systems stand to benefit from accurate image classification models.

d. Interdisciplinary Integration: Collaboration with experts from diverse domains, such as fashion and e-commerce, can result in interdisciplinary projects. Integrating domain-specific knowledge can lead to more contextually relevant and impactful applications.

Addressing Risks:

To mitigate the risks associated with limited computational resources, the project can explore cloud-based solutions or distributed computing. Collaborations with institutions or industry partners could provide access to advanced computing infrastructure.

Continuous monitoring for overfitting risks can be addressed through rigorous validation procedures, early stopping mechanisms, and the incorporation of additional regularization techniques.

Conclusion

As we conclude the report, a vibrant pattern emerges, the profound impact of architectural choices on the performance of deep learning models in the intricate domain of fashion image classification. Embarking on a sartorial exploration, we traversed a spectrum of styles, from the classic elegance of baseline CNNs to the bold intricacies of ResNet, VGG19, and an Inception-inspired masterpiece, all gracefully poised against the Fashion MNIST canvas.

And what a revelation the runway unveils! VGG19, with its deep and disciplined silhouette, rises to the top, surpassing its more ornate counterparts. This triumph demonstrates the potency of simplicity and depth, challenging the conventional wisdom that complexity is the sole path to performance excellence.

Yet, beneath the surface of this elegant victor lies a tapestry of nuanced insights woven through meticulous ablation studies. Each element – network depth, the delicate touch of the loss function, and the skilful application of regularization – plays a vital role in sculpting the model's performance. These findings resonate a profound truth: achieving optimal results demands a delicate balance, a harmonious blend of power and restraint, lest overfitting rear its unwelcome head.

Hyperparameter tuning emerges as the maestro of orchestration. Through fine-tuning the tempo of the learning rate and the momentum of descent, the model finds its perfect rhythm, converging with grace and generalizing with aplomb. This meticulous dance through the hyperparameter space illuminates the path to peak accuracy, a lesson valuable for any aspiring practitioner.

But the true legacy of this project transcends mere architectural appreciation. It stands as a beacon, guiding future research and illuminating diverse applications. The resounding success of VGG19 whispers of the potential for transfer learning, where pre-trained models honed on Fashion MNIST can be gracefully repurposed for a multitude of image classification tasks. Ensemble approaches, a vibrant tapestry of strengths woven from different architectures, promise even greater robustness and performance.

And let us not forget the practical implications, the real-world threads waiting to be woven. Automated product categorization, inventory management that flows like silk, and recommendation systems that whisper personalized style advice – all stand to benefit from the accurate classification models this project has birthed.

In conclusion, this project is not merely an intellectual treatise on deep learning architectures. It is a practical guide, a roadmap for researchers and practitioners alike, navigating the labyrinthine realm of image classification tasks. The insights gleaned from architectural exploration, ablation studies, and hyperparameter tuning stand as valuable currency for all who seek to unravel the complexities of fashion through the power of deep learning.

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	Axar Pandya	21ucs141	*40%*
	Harshit Jain	21ucs090	*5%*

Appendix:

Google Colab Link: [DL Project - Colab]