



Leveraging Deep Learning for Personalized Fashion Recommendations Using Fashion MNIST

Navya Vattikonda

Business Intelligence Engineer
International Medical Group Inc

Anuj Kumar Gupta

Senior Business Analyst
Sea Board Foods

Achuthananda Reddy Polu

Senior SDE
Cloud Hub IT Solutions

Bhumeka Narra

Sr. Software Developer
State Farm

Dheeraj Varun Kumar Reddy Buddula

Software Engineer
Elevance Health Inc

Abstract

People are particularly conscious of their clothing choices since fashion has a big influence on daily life. Large populations are usually recommended fashion goods and trends by specialists via a manual, curated process. On the other hand, e-commerce websites greatly benefit from automatic, personalized recommendation systems, which are becoming more popular. This study introduces a deep learning-based framework for personalized fashion recommendation, utilizing the Fashion-MNIST dataset as the primary data source. The dataset was divided into training and testing sets in a 70:30 ratio to ensure robust evaluation. CNN, Feed forward Neural Networks (FNN), and LSTM models were employed for fashion item classification. Evaluation metrics such as F1-score, recall, accuracy, precision, and loss, along with confusion matrix analysis, were utilized to assess model



performance. Among the tested models, the CNN demonstrated superior performance, achieving 93.99% accuracy, with F1-score, recall, and precision all at 94% and a loss value of 0.2037. Comparative analysis further highlighted the CNN's effectiveness over FNN and LSTM models. These findings demonstrate the promise of CNN architectures for improving the precision and consistency of individualized clothing recommendation systems.

Keywords: Personalized Fashion Recommendations, E-commerce, Fashion Industry, Fashion-MNIST dataset.

I. Introduction

The rapid development of e-commerce has revolutionized how people shop, with online platforms becoming the primary avenue for purchasing goods and services. Within this paradigm, fashion has emerged as a pivotal industry, deeply intertwined with societal identity and personal expression. Unique apparel often reflects individual self-concepts and lifestyles, highlighting cultural and temporal nuances [1]. For the fashion industry, the accurate classification and recommendation of clothing products are critical to addressing consumer demands and optimizing business processes.

However, the vast amount of online clothing information can overwhelm consumers, posing challenges for both merchants and users [2]. Merchants aim to enhance shopping efficiency and cater to diverse preferences, while consumers seek personalized experiences that align with their unique tastes. Personalized recommender systems address this gap by offering tailored suggestions based on user preferences and behavior [3]. These systems have become integral to online shopping, enabling retailers to optimize inventory, boost customer engagement, and foster loyalty. For customers, such systems enhance shopping efficiency, providing a more seamless and satisfying experience.



Data sparsity, the cold start issue, and dependence on prior user input are some of the obstacles that classic recommender systems encounter despite their advantages [4]. These limitations can negatively impact prediction accuracy and user trust. To address these issues, DL-based recommender systems have emerged as a robust alternative [5]. Leveraging their ability to model complex, non-linear user-item relationships, these systems can analyze vast and diverse datasets, including contextual, textual, and visual information.

There have been many changes to enhance recommenders' performance, and deep learning has recently been radically changing recommendation architectures [6]. By successfully navigating challenges presented by traditional models and attaining impressive suggestion quality, recent developments in recommender systems based on deep learning have garnered considerable interest.

A. Motivation and Contribution of the Study

The rapid growth of e-commerce has revolutionized the fashion industry, but consumers often face challenges navigating vast catalogs and finding items that match their preferences, while retailers strive to optimize inventory and provide personalized recommendations. Deep learning offers transformative potential by capturing complex, non-linear relationships between users and items and leveraging diverse data sources, like visual and contextual information, for more accurate and personalized recommendations. This study aims to employ a DL-based approach using the Fashion-MNIST dataset to overcome these challenges, enhancing the efficiency and personalization of fashion recommendations for consumers and optimizing operations for retailers. The key contribution of this study is listed below:

- Utilization of the Fashion-MNIST dataset to validate the effectiveness of a proposed system.



- Implementation of a robust pipeline with resizing, normalization, and one-hot encoding for optimal model input.
- Development of a deep learning framework using CNN, FNN, and LSTM for accurate and tailored fashion recommendations.
- Detailed performance analysis employing metrics like F1-score, recall, precision, accuracy, and confusion matrix.

B. Structure of paper

Here is the outline for the remaining portion of the paper: Section II discusses prior studies on fashion recommendation systems. Section III presents the methods and procedures, whereas Section IV analyses the results. Finally, Section V summarizes the study's findings and suggests future directions.

II. Literature Review

An exciting area of study is fashion suggestion. The intersection of RSs and the fashion industry remains mostly uncharted territory despite the extensive research on RSs. Some of reviews are as follows:

In, Aoki et al. (2019) is to improve the classifier in order to make fashion style estimate more accurate. To train a final SVM-based classifier, experiments were carried out using the Hipster Wars dataset, and to develop a feature extractor, experiments were carried out using the WEARStyle dataset. Classification accuracy was 83.8% when using SSD-based detection following PSPNet-based segmentation, 84.7% when using VAM with ICNet, and 85.1% when using VAM with PSPNet. These methods achieved a higher classification accuracy of 83.0% in the same experiments compared to VAM using full convolutional network (FCN). Controlling the classifier's attention improves classification accuracy, according to the findings [7].



In, Yamamoto and Nakazawa (2019) present their approach to developing CD-CNNs, an enhanced algorithm for recognizing fashion styles. Combining the results of CD-CNNs with an SVM allows them to carry out the categorization. Using the Hipster Wars dataset (with an accuracy of 85.3%) and the FashionStyle14 dataset (with an accuracy of 77.7%), they were able to demonstrate that their strategy is effective and can enhance classification accuracy [8].

In, Jaradat et al. (2018) provide two new approaches to dynamically assist visual categorization with important social media textual material. Through rigorous testing on both the Instagram dataset and the baseline fashion dataset (Deep Fashion), they have shown that their methods can outperform base designs in terms of accuracy, with a 20% improvement. They have achieved a 35% improvement in accuracy for the multi-class multi-label classification problem using Dynamic layers compared to the other model [9]. In, Seo and Shin (2018) suggestion is to use the ImageNet dataset to pre-train the GoogLeNet architecture and then use design features to fine-tune their fine-grained fashion dataset. That will cut down on training time and work well with the short dataset. Final test accuracy findings averaged 62% after 10-fold studies [10]. This study, Li et al. (2017) suggests a system that uses ML to automatically put together clothing. They want to monitor the score component by using the popularity of outfits on fashion-oriented websites. The suggested composition technique was trained and evaluated using a large fashion outfit dataset consisting of 368K fashion pieces and 195K outfits culled from Polyvore. The scoring component of the fashion outfits and the limited composition assignment are both quite difficult, yet they have managed to get an AUC of 85% and a 77% accuracy rate, respectively [11]. In, Chen, Chen and Chen (2014) constructed an innovative dataset for classifying eight types of face shapes, paving the way for further studies on this topic. Additionally, they showcase



experimental findings that demonstrate the suggested face shape characteristics attaining a 94% accuracy rate in face shape categorization. Additionally, they showcase a live demonstration of the fashion picture suggestion algorithm that is reliant on face shape [12].

Table I summarizes key studies on fashion recommendation and classification, highlighting datasets, methodologies, performance, and limitations. It provides insights into advancements in leveraging ML and DL techniques for personalized fashion applications.

References	Dataset	Methodology	Performance	Limitations & Future Work
Aoki et al., 2019	Hipster Wars, WEARStyle	SSD detection with PSPNet segmentation, VAM with ICNet, PSPNet, FCN; SVM-based classifier	Classification accuracies: 83.8% (SSD-PSPNet), 84.7% (VAM-ICNet), 85.1% (VAM-PSPNet), 83.0% (VAM-FCN)	Limited dataset diversity; future work can explore integrating advanced attention mechanisms and datasets with varied fashion categories.
Yamamoto and Nakazawa, 2019	Hipster Wars, FashionStyle14	Component-dependent CNNs (CD-CNNs) with semantic segmentation, pose estimation, and SVM classification.	Classification accuracies: 85.3% (Hipster Wars), 77.7% (FashionStyle14)	Limited exploration of body postures; future work can include improved body part segmentation algorithms and diverse datasets for broader applicability.
Jaradat et al., 2018	Instagram, DeepFashion	Adaptive neural pruning (Dynamic Pruning), Dynamic Layers for attribute-based classification	Accuracy improved by ~20% compared to base architectures; Dynamic Layers achieved 35% accuracy in multi-class multilabel classification.	Heavy reliance on social media text content; future work could address handling noisy or missing textual data and expanding the framework for more nuanced classifications.



Seo and Shin, 2018	Custom fine-grained fashion dataset, ImageNet	Pre-training GoogLeNet on ImageNet and fine-tuning on design attribute-based fashion dataset	Final test accuracy: 62%	Small dataset size limits generalizability; future work can focus on incorporating larger datasets and leveraging transfer learning with more sophisticated architectures.
Li et al., 2017	Polyvore (195K outfits, 368K fashion items)	Multimodal multi-instance deep learning system for fashion outfit scoring and composition	AUC of 85% for scoring component; 77% accuracy for constrained composition task	Limited metadata consideration; future work could involve incorporating more contextual and user-specific data to enhance recommendation quality.
Chen, Chen, and Chen, 2014	Custom face shape dataset	Face shape classification using novel face shape features and a prototype face-shape-based recommendation system	94% accuracy for face shape classification	The dataset is limited to eight face-shape categories; future work could expand the dataset and improve classification techniques.

III. Methodology

This study adopts a structured approach to designing a personalized fashion recommendation system using deep learning techniques. The Fashion-MNIST dataset serves as the primary data source, comprising images that were preprocessed through resizing to 28x28 pixels, grayscale conversion, pixel value normalization, and one-hot encoding of labels. To make it easier to build and evaluate models, the dataset was split into 70:30 training and testing subsets. Deep learning architectures, including CNN, FNN, and LSTM models, were employed to analyze and classify fashion items. Performance assessment used confusion

matrices and measures, including accuracy, precision, recall, and F1-score, to measure the efficacy of the model. This comprehensive design ensures the creation of a system capable of delivering accurate and tailored fashion recommendations. The flow chart for applied methodology is shown in Figure 1.

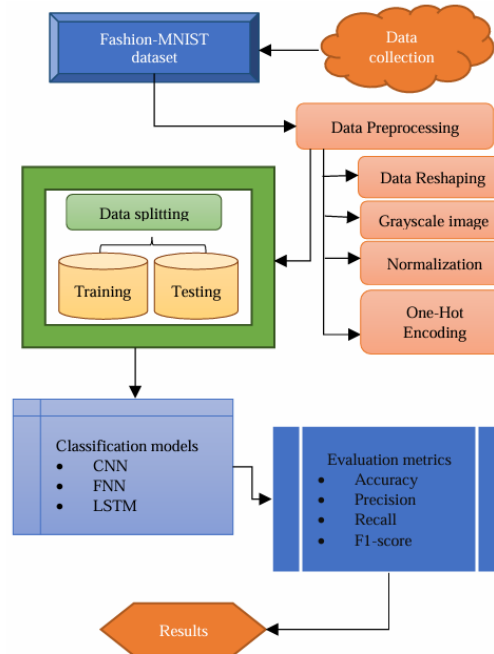


Fig. 1. Flowchart for Fashion recommendation system

The overall process of the data flow diagram in-depth analysis is described below:

Data Collection

The dataset utilized in this study, known as Fashion-MNIST, was sourced from the KAGGLE repository. There are 60,000 training photos and 10,000 test images in it. From T-shirts and tops to ankle boots, each greyscale picture is sorted into 10 distinct groups. The F-MNIST dataset is shown in Figure 2 with example images:

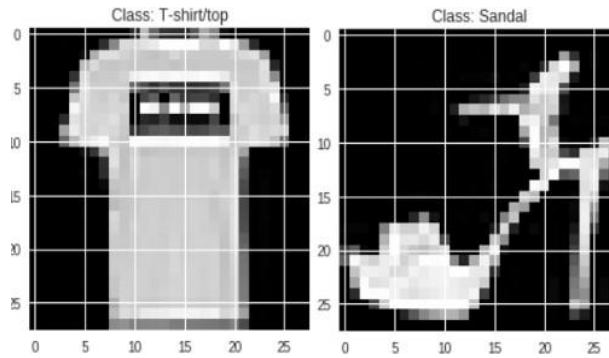


Fig. 2. Sample images in F-MNIST dataset

Figure 2 shows the F-MNIST dataset image sample. a T-shirt and a sandal.

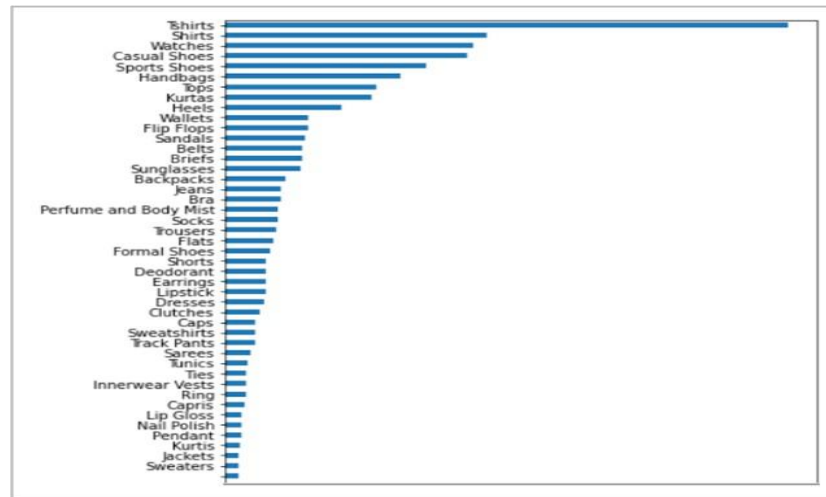


Fig. 3. Fashion Outfit Categories

Figure 3 displays a horizontal bar chart showing the frequency of various product categories, likely from an e-commerce dataset. The most frequently occurring categories are "T-shirts," "Shirts," "Watches," and "Casual Shoes," with their bars extending the furthest to the right, indicating high counts. Conversely, categories like "Nail Polish," "Pendants," and "Sweaters" appear less frequently, as reflected by their shorter bars. This chart provides insight into product category distribution or popularity.



Data Preprocessing

A clean data set is the goal of data preparation, which involves transforming raw data. Prior to running the algorithm on the dataset, it undergoes preprocessing to identify and remove any inconsistencies, such as missing values or noisy data. The key preprocessing steps utilized in this study are as follows:

- **Data reshaping:** Image resizing is essential for displaying media at various resolutions and aspect ratios. In this study, the images were resized to 28X28 dimensions.
- **Grayscale the Image:** The raw pixel values of the images range from 0 to 255, representing different

Data Normalization

Normalizing the pixel values ensures that all input features are on the same scale, preventing the model from giving undue weight to higher values. This normalization improves the convergence rate and stability of the model during training.

D. One- hot encoding

The labels have been labeled using the one-hot encoding approach. Here, they convert the integer label into a vector where each element is a '1' representing the associated label position and all the other elements are '0'.

Data Splitting

In the complete dataset that was utilized in this study, 70% was allocated for training, while the remaining 30% was designated for testing. The model underwent training with the training dataset, and subsequently, testing was conducted using the testing dataset.



Proposed Convolutional neural networks (CNN) Model

Deep learning techniques known as CNNs take in pictures as input and use filters and kernels to extract information. The $f \times f$ filter is used to convolutionally train a single feature on an entire $N \times N$ image. After every action, the window scrolls to reveal the learnt features from the feature maps. The feature maps record the image's local receptive field and use shared biases and weights to function [13]. Convolution operation can be expressed as follows (1):

$$y = f(W_k * x + b_k) \quad (1)$$

where:

- y is the output (feature map or classification result).
- f is the activation function (e.g., ReLU, sigmoid, softmax).
- W_k is the weight (kernel) for layer k .
- b_k is the bias term for layer k .
- $*$ denotes the convolution operation (or pooling if applied).
- x is the input (either the image data or feature map from the previous layer)

Model Evaluation

Model evaluation is a subprocess of the modeling process[14]. Accuracy, precision, recall, and f1-score, in addition to the confusion matrix, are some of the metrics used to evaluate the models in this research. In ML, a confusion matrix stands in for a classification model's accuracy and is used to assess its performance. The following classes are listed in below:

- **TP (True Positive):** The amount of positive samples that were accurately anticipated.
- **FP (False Positive):** The total amount of samples that were wrongly thought to be negative.



- **FN (False Negative):** Expected to have a negative value but has a positive actual value.
- **TN (True Negative):** The quantification of samples that were accurately predicted as negative.

Accuracy: The accuracy rate is the percentage of forecasts that were right out of all the predictions made. To determine accuracy, use the formula in Equation (2).

$$Accuracy = \frac{TP+TN}{TP+TN+FN+FP} \quad (2)$$

Recall: The proportion of class members who were properly categorized out of all the class members. Equation (3) represents the formula for calculating recall.

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

Precision: The proportion of examples accurately identified as belonging to a given class divided by the total number of occurrences in that class. Equation (4) represents the formula for calculating precision.

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

F1-Score: When Precision and Recall are harmonically averaged, the result is the F1-score. The formula for computing the F1-score is given by Equation (5)

$$F1 - Score = \frac{2 \times precision \times recall}{precision + recall} \quad (5)$$

These matrices used for evaluate the model efficiency for fashion recommendation system.



IV. Result Analysis and Discussion

The laptop used for all the trials in this research has an Intel Core (TM) i5-6300HQ CPU running at 2.30GHz x 4, 16GB of DDR3 RAM, and an NVIDIA GeForce GTX 960M 4GB graphics card. The study shows results for the proposed model through graphical displays representing performance metrics to provide substantial demonstrations of its effectiveness. Table II provides the results obtained from the CNN model. Several different models were compared to the suggested one, including FNN[15] and LSTM[16], as displayed in Table III.

Table ii. Findings of Cnn Model For Fashion

Recommendation System on The Fashion-Mnist Dataset

Performance Matrix	Convolutional Neural Network (CNN)
Accuracy	93.99
Precision	94
Recall	94
F1-score	94
Loss	0.2037

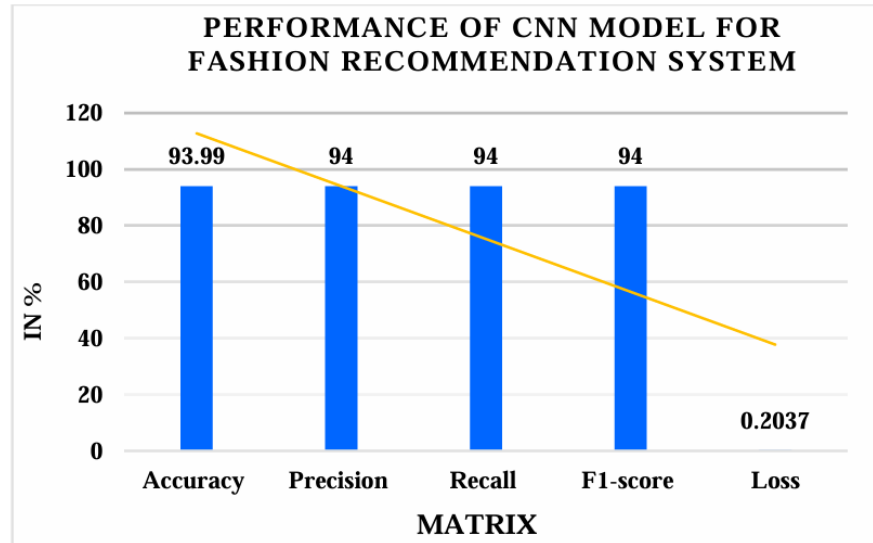


Fig. 4. Bar Graph for Performance of CNN Model

The CNN model's performance indicators for the fashion recommendation are shown in Table II and Figure 4. An astounding 93.99% accuracy was attained by the CNN, with precision, recall, and F1-score all approaching 94%. The model's loss value was recorded at 0.2037, demonstrating its effectiveness in accurately classifying fashion items while maintaining a strong balance between precision and recall. These results highlight CNN's potential for high performance in fashion recommendation tasks.

Class	Label	0	1	2	3	4	5	6	7	8	9
T-shirt/top	0	898	0	13	7	2	1	72	0	7	0
Trouser	1	0	988	0	7	1	0	2	0	2	0
Pullover	2	14	0	902	6	36	0	41	0	1	0
Dress	3	15	1	10	932	12	0	29	0	1	0
Coat	4	0	0	17	20	932	0	27	0	4	0
Sandal	5	0	0	0	0	0	995	0	3	0	2
Shirt	6	75	0	29	19	54	0	815	0	8	0
Sneaker	7	0	0	0	0	0	6	0	984	1	9
Bag	8	0	0	0	1	0	0	0	0	999	0
Ankle boot	9	0	0	0	0	0	8	0	37	1	954

Fig. 5. Confusion matrix for CNN

Figure 5 shows the confusion matrix evaluating a performance of a classification model. A table represents a confusion matrix for a classification task involving 10 classes, such as clothing items. Each row corresponds to the true class, and each column shows how many instances were predicted as each class. For example, 898 instances of "T-shirt/top" were correctly classified, while 72 instances of "T-shirt/top" were misclassified as "Ankle boot."

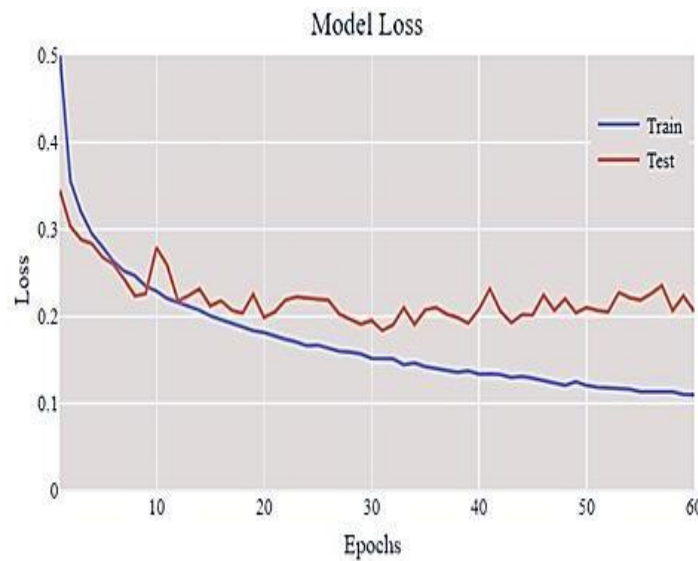


Fig. 6. Train-Test Loss curves for CNN Model

The CNN model's train and test loss curves across 60 training epochs are shown in Figure 6. The test loss begins low, rises, and then falls, but the training loss begins high and progressively declines throughout the epochs. This suggests that the model is initially overfitting on the training data but ultimately improves its generalization to the test set as training goes on.

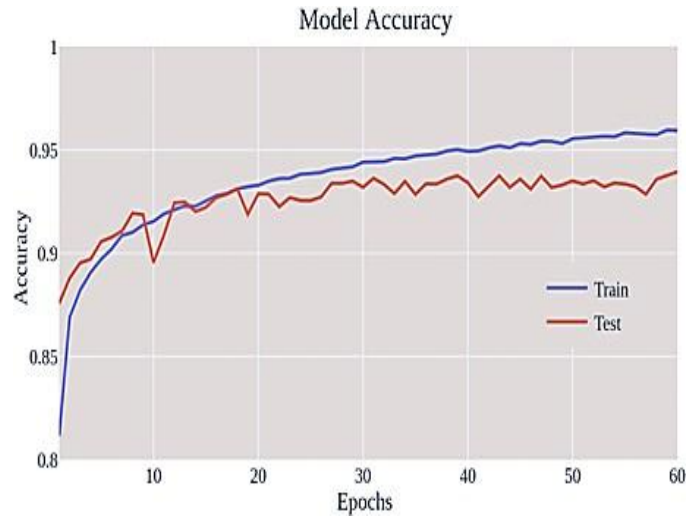


Fig. 7. Train-Test Accuracy curves for CNN Model

Figure 7 displays the train-test accuracy curves for a CNN model spanning 60 training epochs. Training results in an accuracy that begins at 0.85 and reaches 0.97 at the conclusion. The test accuracy starts higher at 0.9 but fluctuates more, ending around 0.92. This suggests the model initially overfits the training data but eventually generalizes better to the test set.

Table III. Comparison Between Cnn And Other Models Performance On The Fashion-Mnist Dataset

Models	Accuracy	Precision	Recall	F1-score
CNN	93.99	94	94	94
FNN	89.06	89	89	89
LSTM	88.26	88.56	88.87	88.56

Table III compares a performance of a models on the Fashion-MNIST dataset. The CNN outperforms both the FNN and LSTM models across all metrics, achieving an accuracy of 93.99% and F1-score, recall, and precision of all94%. In comparison, the FNN scored 89.06% in accuracy, with F1 score, recall, and



precision all at 89%. The LSTM model, while slightly behind the FNN, achieved an accuracy of 88.26%, with recall 88.87%, precision 88.56%, and F1 score 88.56%. These results indicate that CNN is the most effective model for fashion classification on this dataset, surpassing both FNN and LSTM in overall performance.

V. Conclusion And Future Scope

Particularly in the realm of online purchasing, recommendation algorithms have become indispensable. A lot of people have been paying attention to recommendation systems that are employed in many fields, with a particular emphasis on apparel and fashion. Considering customers' personalized fashion choices makes the challenge much more fascinating and complex. This research shows that using the Fashion-MNIST dataset, DL models can effectively provide tailored fashion recommendations. CNN performed the best out of all the models that were evaluated, with an astounding accuracy of 93.99%, along with precision, recall, and F1-score of 94%. The LSTM model achieved an accuracy 88.26% and the FNN model achieved an accuracy 89.06%, respectively.

The CNN model has the ability to classify fashion items accurately and reliably due to its outstanding performance across all measures. Findings also show that normalization, scaling, and greyscale conversion are crucial preprocessing steps for improving model performance. The recommendation system will be fine-tuned in subsequent work by investigating more complex architectures and making use of bigger, real world datasets to increase its flexibility and scalability.

References

1. Brynjolfsson, E., & McAfee, A. (2017). *Machine, Platform, Crowd: Harnessing Our Digital Future*. W. W. Norton & Company.



2. Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review*, 96(1), 108–116.
3. Chen, M., Mao, S., & Liu, Y. (2014). Big data: A survey. *Mobile Networks and Applications*, 19(2), 171–209. <https://doi.org/10.1007/s11036-013-0489-0>
4. Rajkomar, A., Dean, J., & Kohane, I. (2019). Machine learning in medicine. *New England Journal of Medicine*, 380(14), 1347–1358. <https://doi.org/10.1056/NEJMr1814259>
5. McKinsey Global Institute. (2020). *The State of AI in 2020*. <https://www.mckinsey.com>
6. Wamba-Taguimdje, S.-L., Wamba, S. F., Kala Kamdjoug, J. R., & Tchatchouang Wanko, C. E. (2020). Influence of artificial intelligence (AI) on firm performance: The business value of AI-based transformation projects. *Business Process Management Journal*, 26(7), 1893–1924. <https://doi.org/10.1108/BPMJ-10-2019-0411>
7. Ghosh, R. (2021). AI in post-pandemic business recovery: Lessons from global enterprises. *Journal of Business Strategy*, 42(5), 345–359.
8. Shrestha, Y. R., Ben-Menahem, S. M., & von Krogh, G. (2019). Organizational decision-making structures in the age of artificial intelligence. *California Management Review*, 61(4), 66–83. <https://doi.org/10.1177/0008125619862257>
9. Daugherty, P. R., & Wilson, H. J. (2018). *Human + Machine: Reimagining Work in the Age of AI*. Harvard Business Review Press.
10. Ransbotham, S., Kiron, D., Gerbert, P., & Reeves, M. (2018). Reshaping business with artificial intelligence. *MIT Sloan Management Review*, 60(1), 1–17.
11. Mahra, Mr Anil Kumar. "STUDY OF INVESTMENT AWARENESS AMONG WORKING WOMEN IN BHOPAL."



12. Mahra, Mr Anil Kumar. "FINANCIAL LITERACY AND PATTERN OF SAVINGS, INVESTMENT BEHAVIOR OF WOMEN TEACHING FACULTIES IN SAGAR REGION. AN EMPIRICAL ASSESSMENT."
13. Mahra, Mr Anil Kumar. "ESG INDEX IS GOOD FOR SOCIALLY RESPONSIBLE INVESTOR IN INDIA." *Global Journal of Multidisciplinary Studies* 8.6 (2019).
14. Mahra, Anil Kumar. "A Strategic Approach to Information Technology Management." (2019).
15. Kumar, Anil, et al. "Integrated Nutrient Management Practices for Sustainable Chickpea: A Review." *Journal of Advances in Biology & Biotechnology* 28.1 (2025): 82-97.
16. S. Shen, "Image Classification of Fashion-MNIST Dataset Using Long Short-Term Memory Networks," 2017.
17. Chinta, P. C. R., Katnapally, N., Ja, K., Bodepudi, V., Babu, S., & Boppana, M. S. (2022). Exploring the role of neural networks in big data-driven ERP systems for proactive cybersecurity management. *Kurdish Studies*.
18. Routhu, K., Bodepudi, V., Jha, K. M., & Chinta, P. C. R. (2020). A Deep Learning Architectures for Enhancing Cyber Security Protocols in Big Data Integrated ERP Systems. *Available at SSRN 5102662*.
19. Moore, C. (2023). AI-powered big data and ERP systems for autonomous detection of cybersecurity vulnerabilities. *Nanotechnology Perceptions*, 19, 46–64.
20. Bodepudi, V., & Chinta, P. C. R. (2024). Enhancing Financial Predictions Based on Bitcoin Prices using Big Data and Deep Learning Approach. *Available at SSRN 5112132*.



21. Chinta, P. C. R. (2023). The Art of Business Analysis in Information Management Projects: Best Practices and Insights. *DOI: 10*.
22. Chinta, P. C. R., & Katnapally, N. (2021). Neural Network-Based Risk Assessment for Cybersecurity in Big Data-Oriented ERP Infrastructures. Neural Network-Based Risk Assessment for Cybersecurity in Big Data-Oriented ERP Infrastructures.
23. Katnapally, N., Chinta, P. C. R., Routhu, K. K., Velaga, V., Bodepudi, V., & Karaka, L. M. (2021). Leveraging Big Data Analytics and Machine Learning Techniques for Sentiment Analysis of Amazon Product Reviews in Business Insights. *American Journal of Computing and Engineering*, 4(2), 35–51.
24. Chinta, P. C. R., Moore, C. S., Karaka, L. M., Sakuru, M., Bodepudi, V., & Maka, S. R. (2025). Building an Intelligent Phishing Email Detection System Using Machine Learning and Feature Engineering. *European Journal of Applied Science, Engineering and Technology*, 3(2), 41–54.
25. Moore, C. (2024). Enhancing Network Security With Artificial Intelligence-Based Traffic Anomaly Detection in Big Data Systems. *Available at SSRN 5103209*.
26. Chinta, P. C. R., Moore, C. S., Karaka, L. M., Sakuru, M., & Bodepudi, V. (2025). Predictive Analytics for Disease Diagnosis: A Study on Healthcare Data with Machine Learning Algorithms and Big Data. *J Cancer Sci*, 10(1), 1.
27. Chinta, P. C. R., Jha, K. M., Velaga, V., Moore, C., Routhu, K., & Sadaram, G. (2024). Harnessing Big Data and AI-Driven ERP Systems to Enhance Cybersecurity Resilience in Real-Time Threat Environments. *Available at SSRN 5151788*.



28. Chinta, P. C. R. (2023). Leveraging Machine Learning Techniques for Predictive Analysis in Merger and Acquisition (M&A). *Journal of Artificial Intelligence and Big Data*, 3(1), 10–31586.
29. Chinta, P. C. R. (2022). Enhancing Supply Chain Efficiency and Performance Through ERP Optimisation Strategies. *Journal of Artificial Intelligence & Cloud Computing*, 1(4), 10–47363.
30. Chinta, P. C. R., & Karaka, L. M. **Agentic AI and Reinforcement Learning: Towards More Autonomous and Adaptive AI Systems.**
31. Sadaram, G., Karaka, L. M., Maka, S. R., Sakuru, M., Boppana, S. B., & Katnapally, N. (2024). AI-Powered Cyber Threat Detection: Leveraging Machine Learning for Real-Time Anomaly Identification and Threat Mitigation. *MSW Management Journal*, 34(2), 788–803.
32. Krishna Madhav, J., Varun, B., Niharika, K., Srinivasa Rao, M., & Laxmana Murthy, K. (2023). Optimising Sales Forecasts in ERP Systems Using Machine Learning and Predictive Analytics. *J Contemp Edu Theo Artific Intel: JCETAI-104*.
33. Sadaram, G., Sakuru, M., Karaka, L. M., Reddy, M. S., Bodepudi, V., Boppana, S. B., & Maka, S. R. (2022). Internet of Things (IoT) Cybersecurity Enhancement through Artificial Intelligence: A Study on Intrusion Detection Systems. *Universal Library of Engineering Technology*, (2022).
34. Jha, K. M., Velaga, V., Routhu, K. K., Sadaram, G., & Boppana, S. B. (2025). Evaluating the Effectiveness of Machine Learning for Heart Disease Prediction in Healthcare Sector. *J Cardiobiol*, 9(1), 1.
35. Maka, S. R. (2023). Understanding the Fundamentals of Digital Transformation in Financial Services: Drivers and Strategic Insights. *Available at SSRN 5116707*.



36. Karaka, L. M. (2021). Optimising Product Enhancements: Strategic Approaches to Managing Complexity. *Available at SSRN 5147875*.
37. Kishan Kumar Routhu, A. D. P. Risk Management in Enterprise Merger and Acquisition (M&A): A Review of Approaches and Best Practices.
38. Routhu, Kishan Kumar, Katnapally, Niharika, & Sakuru, Manikanth. (2023). Machine Learning for Cyber Defense: A Comparative Analysis of Supervised and Unsupervised Learning Approaches. *Journal for ReAttach Therapy and Developmental Diversities*, 6. 10.53555/jrtd.v6i10s(2).3481.
39. Kalla, D., Smith, N., Samaah, F., & Polimetla, K. (2022). Enhancing Early Diagnosis: Machine Learning Applications in Diabetes Prediction. *Journal of Artificial Intelligence & Cloud Computing*, SRC/JAICC-205. DOI: [doi.org/10.47363/JAICC/2022\(1\), 191, 2–7](https://doi.org/10.47363/JAICC/2022(1), 191, 2-7).
40. Chinta, Purna Chandra Rao, & Moore, Chethan Sriharsha. (2023). Cloud-Based AI and Big Data Analytics for Real-Time Business Decision-Making. 36, 96–123. 10.47363/JAICC/2023.
41. Kuraku, D. S., & Kalla, D. (2023). Phishing Website URLs Detection Using NLP and Machine Learning Techniques. *Journal on Artificial Intelligence - Tech Science*.
42. Krishna Madhav, J., Varun, B., Niharika, K., Srinivasa Rao, M., & Laxmana Murthy, K. (2023). Optimising Sales Forecasts in ERP Systems Using Machine Learning and Predictive Analytics. *J Contemp Edu Theo Artific Intel: JCETAI-104*.
43. Jha, K. M., Velaga, V., Routhu, K., Sadaram, G., Boppana, S. B., & Katnapally, N. (2025). Transforming Supply Chain Performance Based on Electronic Data Interchange (EDI) Integration: A Detailed Analysis. *European Journal of Applied Science, Engineering and Technology*, 3(2), 25–40.



44. Kuraku, D. S., & Kalla, D. (2023). Phishing Website URLs Detection Using NLP and Machine Learning Techniques. *Journal on Artificial Intelligence - Tech Science*.
45. Jha, K. M., Velaga, V., Routhu, K. K., Sadaram, G., & Boppana, S. B. (2025). Evaluating the Effectiveness of Machine Learning for Heart Disease Prediction in Healthcare Sector. *J Cardiobiol*, 9(1), 1.
46. Kishan Kumar Routhu, A. D. P. Risk Management in Enterprise Merger and Acquisition (M&A): A Review of Approaches and Best Practices.
47. Kalla, D., Mohammed, A. S., Boddapati, V. N., Jiwani, N., & Kiruthiga, T. (2024, November). Investigating the Impact of Heuristic Algorithms on Cyberthreat Detection. In *2024 2nd International Conference on Advances in Computation, Communication and Information Technology (ICAICCIT)* (Vol. 1, pp. 450–455). IEEE.
48. Bodepudi, V. (2023). Understanding the Fundamentals of Digital Transformation in Financial Services: Drivers and Strategic Insights. *Journal of Artificial Intelligence and Big Data*, 3(1), 10–31586.
49. Kalla, D., Smith, N., & Samaah, F. (2025). Deep Learning-Based Sentiment Analysis: Enhancing IMDb Review Classification with LSTM Models. *Available at SSRN 5103558*.
50. Jha, K. M., Bodepudi, V., Boppana, S. B., Katnapally, N., Maka, S. R., & Sakuru, M. Deep Learning-Enabled Big Data Analytics for Cybersecurity Threat Detection in ERP Ecosystems. 2023.
51. Kalla, D., Samaah, F., Kuraku, S., & Smith, N. (2023). Phishing Detection Implementation Using Databricks and Artificial Intelligence. *International Journal of Computer Applications*, 185(11), 1–11.



52. Boppana, S. B., Moore, C. S., Bodepudi, V., Jha, K. M., Maka, S. R., & Sadaram, G. AI and ML Applications in Big Data Analytics: Transforming ERP Security Models for Modern Enterprises.
53. Sreeramulu, M. D., Mohammed, A. S., Kalla, D., Boddapati, N., & Natarajan, Y. (2024, September). AI-driven Dynamic Workload Balancing for Real-time Applications on Cloud Infrastructure. In *2024 7th International Conference on Contemporary Computing and Informatics (IC3I)* (Vol. 7, pp. 1660–1665). IEEE.
54. Kalla, D., & Samaah, F. (2023). Exploring Artificial Intelligence and Data-Driven Techniques for Anomaly Detection in Cloud Security. *Available at SSRN 5045491*.
55. Kalla, D., Smith, N., & Samaah, F. (2023). Satellite Image Processing Using Azure Databricks and Residual Neural Network.