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Bias-Free Hybrid Explainable Recommendation System with Role-Based Dashboard

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Abstract: Abstract: The abstract outlines the challenge of understanding the necessity of the creation of recommender systems in a rapidly changing online marketplace. Recommender systems help customers to make sense of the overwhelming amount of choices available on the internet, however, many traditional recommendation models do not provide an explicit bias indicator and therefore often produce recommendations that favour the more popular products, without any insight as to how those recommendations are generated. A number of empirical studies conducted recently have demonstrated that the association between biased exposure, black-box deep learning algorithms and the way in which items from the long-tail category are treated unequally leadstonegativeuserexperiencesandprohibitslong-tailsellers frombeingabletocompetewithlargere-commerceplatforms. This paper will present an alternative method of creating a recommender system that eliminates the bias associated with the traditional collaborative filtering and content-based methods. Specifically, the Bias-Independent Hybrid Explanation based Recommender System will utilise deep neural networks as an additional source of information to produce higher quality recommendations and minimise the chances of placing products into unfair exposure patterns. In addition, the proposed method will also incorporate SHAP (SHapley Additive exPlanations) and the LIME (Local Interpretable Model-agnostic Explanations) model of explanationsinordertoimprovethetransparencyofthemodel. In addition, this paper includes the introduction of a Fairness-Aware Re-Ranking method and an Exposure Balance Mechanism to deal with the issues associated with fairness.
Keywords: Recommender Systems, Hybrid Recommendation, Fairness in AI, Popularity Bias, Explainable AI (XAI), SHAP Explanations, LIME, Exposure Fairness, Neural Collaborative Filtering, Role-Based Dashboard, Responsible AI.

I. INTRODUCTION

For many digital services and marketplaces, the recommendationenginesusedbyonlineretailershavebecome a critical component of providing an enhanced customer experienceandfulfillingcustomerneeds.Thesheeramountof information available on the internet makes it increasingly difficult for end users to identify relevant products/services from a wide variety of product/service offerings. As a result, recommendations are critical to providing a more satisfying end-user experience while creating revenues for the business [1], [9]. Traditional recommendation engines — such as collaborativefiltering(CF)andcontent-basedfiltering(CBF) have become popular; however, several recent studies suggest that CF and CBF are subject to many limitations including popularitybias,datasparsity,andlackoftransparency[2],[5], [6], [8].

Popularity bias creates an environment whereby a smaller supplier/vendor or long-tail product will seldom receive substantial visibility due to the fact that a recommendation engine'salgorithmsfocusonrecommendingalreadysuccessful products, which creates inequitable access and existence for smaller suppliers and products [2], [4], [7]. This bias has a significantnegativeimpactonhowequitablyrecommendations are distributed on eCommerce platforms, creating differing levels of opportunity for all suppliers/vendors and in many cases; all creators of content on the internet; thus negatively impacting overall fairness or equality in the ecommerce marketplace. In addition to popularity bias, it is important to considerthatthere maybebiasesintroducedhistoricallyinthe data that is used to develop recommendation systems. Several researchers have demonstrated that recommender systems develop bias toward or against certain demographic groups and/orbehavioursduetohistoricalinteractionpatterns[1],[3], [5].Thismeansthatwhenonedemographicgroupconsistently interacts with a recommendation system less than another group, there will be evidence that the former is more likely to receivelower-qualityrecommendationsthanifbothgroupshad the same level of interaction.

Inadditiontothepopularitybiasissue,anothersignificantissue with using deep learning models for recommendation systems isthefactthatmanyofthedeeplearning-basedrecommenders, specificallytheNCFand sequentialrecommenders,actasblack boxes. As such, it is difficult for end users of the recommendation systemto gainanunderstandingof whythey receiverecommendationsfromthesetypesofrecommendation system.

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A. IntroductionandRationale

The rise in the quantity of digital platforms, online marketplaces,andmobileapplicationsavailableinIndiaduring recentyearshasresultedinanincreaseintheneedforAI-based, personalised recommendation systems. With there being so much content available on platforms like Flipkart, Meesho, Hotstar,etc.,usershavecometoexpectarecommendation systemthatunderstandstheir individual interestsand provides appropriate recommendations based on that knowledge, from enormous digital catalogues. By identifying the most relevant itemsfromthemillionsofproductsavailable,recommendation systems can assist customers in filtering through information overloads while increasing levels of customer satisfaction [1].

Inaddition,asrecentstudieshaveshown,mostoftheobstacles facing recommendation systems today can have a negative effect on decision-making processes based on perceived fairness, transparency, and ultimately trust over the long term insaidsystems. Asignificantchallengeispopularitybias where algorithms tend to provide more exposure to already popular/largest vendors' items and less exposure to smaller/regional/new vendors—something that has been widely documented in academic publications regarding e-commerceplatforms[2],[6],[7],[8].Thishasdireimplications for numerous MSMEs, handicraft sellers, rural artisans, and small businesses in India whose products will not be able to obtain an appropriate level of visibility on large e-commerce platforms.

Furthermore, the second-most significant challenge facing recommendation systems is that they are frequently not explainable. A majority of today's Deep Learning recommendersystemsoperateas"BlackBox"models,thereby preventing users fromunderstanding the rationale behind why a specific product was recommended to them

The first goal of this project is to develop a Hybrid Recommendation Engine. This involves combining Collaborative Filtering, Content-Based Filtering, and Light-weight Deep Learning techniques to create a Hybrid Recommendation Engine that provides the user with more Accurate and Diverse Recommendations than traditional Single Model Recommendation Systems.

1) Popularity Bias Recognition & Mitigation: To accomplish this, Fairness Aware Techniques, such as Exposure-Based Adjustment, Fair Sampling & Re-Ranking, will be developed to reduce the disproportionate visibility of Highly Popular Items and Increase Fair Exposure for Small and/or Emerging Sellers.
2) Incorporation of Explainable AI (XAI): Integrating the SHAP/LIME based Explanation Methods into the Recommendation System to provide Users and System AdministratorswithClear,Human-UnderstandableReasoning foreachrecommendationwillimproveTrustandInterpretable Results.
3) Role-Based Governance Dashboards: Role-Based Governance Dashboards for Users, Project Managers and Administrators will enable Users to track and view Fairness Metrics; Project Managers to analyse Model Performance and Exposures, and Administrators to manage the Systemin Real-TimetoensureMulti-StakeholderFairnessinaccordance with previous work.
4) In order to ensure that AI systems comply with ethical considerationsandregulatoryrequirements,modificationswill be made to incorporate fairness principles as outlined by the Responsible AI Framework, ensure compliance with India's Digital Personal Data Protection Act (2023), and adhere to guidelines set forth by NITI Aayog (National Institute for Transformation of India).
5) Once the AI system is wholly operational, a thorough assessmentoftheperformancewillbeconductedbasedupona variety of metrics related to accuracy, fairness, and explainability. These metrics will include such variables as: precision, Normalized Discounted Cumulative Gain (NDCG), fairnessindex,exposuredistribution,andexplanationstability. Data will be collected from these metrics to evaluate how successfully the AI system achieves a balance between both accuracy and fairness.
6) Toallowforthegrowthoftheapplicationbeyondaprototype phase and prepare for a future deployment at a scalable level withinIndianE-Commerceindustry,anewarchitectureforthe AI system has been created, using modern open-source technologies (including Next.js, Node.js, MongoDB, and FastAPI)thatareappropriateforimplementationintotheIECE (Indian E-commerce Commerce Ecosystem).

B. Scopeofthe Project

This project encompasses the design, implementation, and evaluation of a bias-free, hybrid and explainable recommendationsystemthatisspecificallydesignedtobeused inane-commerceenvironment.Theproject'sgoalistoachieve a balance between accurate, fair, and interpretable recommendations while providing convenient governance features that are transparent to multiple stakeholders. The project's primaryboundaries and areas covered are as follows:

1) System Coverage

The system is comprised of the following complete pipeline components: • A hybrid recommender that includes the combination of Collaboration Filtering (CF), Content-Based Filter(CBF)andshallowdeeplearningmodels[9].•Fairness-aware components that provide bias detection and correction, as well as re-ranking capabilities [2], [3], [4], [6], [8].

• Explainability components that generate interpretable explanations for both users and administrators using SHAP or LIME. • A role-based dashboard used by Users, Project Managers and Admins alike for tracking behaviors of the system.

2) FunctionalScope

Thefollowingitemsrepresentwhatfeatureswillbesupported by the project:

- PersonalisedTop-Kproductrecommendations.
- Fairness Monitoring via vendor/category Exposure Metrics [4],[5].
- Versioning of models, hyperparameter control, retraining options for administrators.
- Capturing user feedback (likes, dislikes, and not interested) to complete the feedback loop on recommendations. •
- Real-timeexplanationsforeachrecommendedproduct item that improve user confidence.

3) Dataset&Context

The system leverages publicly available e-commerce datasets for conducting research around fairness (i.e., datasetssuchasAmazon-styledatasetsbasedonsyntheticattributesofusersfromIndia)[1],[6].Thesystemalsohasadditionalsyntheticmetadatathatcanbeusedtorepresent Indian sellers, MSMEs, and product_categories on a regionalbasistofurthertesttheimpactofdifferent variable levels on the fairness of the system. Finally, the system includes interaction (click-view-purchase) logs as part of its training and testing data**.**

4) Scopeof Technology

The Technological Toolbox for the project consists of modern, open-source, industry-standard tools:

- FrontendTechnology:Next.js,React,TypeScript
- BackendTechnology:Node.js,Express.js
- DatabaseTechnology:MongoDB
- Machine Learning Microservice Technology: Python (FastAPI) These technologies will enable users to build scalable and affordable solutions suitable for entrepreneurs starting a business in India, as well as foracademic institutionsand e-commercecompanies with roots in the Indian marketplace.

C. System Evaluation

Theevaluationofthissystemwillassess:

1) Accuracy Metrics - Precision@K and Normalized Discounted Cumulative Gain (NDCG)
2) Fairness Metrics - Exposure Fairness and Group Imbalance Reduction [3],[4];
3) Explainability Metrics - Stability of SHAP Features (Stable) and Human Interpretability.
4) Scope Constraints (Limitations) This project is limited in the following ways:
5) The project does not include large-scale, real-time streaming recommender systems.
6) The project cannot incorporate sensitive fairness attributes (e.g., caste and religion) because of legal and ethical issues related to India's Data Protection and Data Privacy Act.
7) The project is designed for non-commercial cloud platformimplementations(asimpledemodeployment only).

II. LITERATURE REVIEW

A. OverviewofRecommendationSystems

Overview of Recommendation Systems Using recommendationsystems,onecanidentifyrelevantitemsfrom vast quantities of digitally available items. Traditionally, two techniques existed to provide recommendations: collaborative filtering,whichprovidesrecommendationsbasedonuser-item interaction history [9], and content-based filtering, which providesproductrecommendationsbasedonauserprofileand product attributes. Hybrid systems use a combination of these two techniques to provide improved accuracy and diversification of products being recommended [10].

Modern day recommendation systems within eCommerce provide the discovery of new products, allow users to interact withbrandsmoreeffectively,andprovidegenerateincomefor the business, all while managing vast amounts of data and processing the data in real-time [1].

B. HybridRecommendationTechniques

Hybrid recommendation models integrate CF, CBF, and deep learning to address limitations such as cold start, sparsity, and limited diversity. Matrix factorisation methods [9], neural models like NCF [10], recurrent models like GRU4Rec and attention-based SASRec have improved recommendation quality.

Recent surveys highlight that hybrid designs offer better robustness and adaptability across domains.

C. BiasandFairnessinRecommendation

Oneoftheissueswithrecommendersystemstodayisthatthey reinforce popularity bias and expose people to things in an unfair way [2],[3],[6]. This leads to a negative effect on small sellers(duetolessitemdiversity)aswellasadisadvantagefor certaingroupsofusers(thosewithveryfewitemsbeingshown each week).

To combat the problems of exposure discrimination, researchers are developing tools to help balance these things between different stakeholder groups. Fairness-Aware Ranking,ExposureBalancing,andGroupFairnessMetricsare someofthetoolsbeingproposedbyresearcherstoreducethese types of harmful recommendations and promote fairness [4],[5],[8]. Studies that have been conducted in this area are now leaning towards Multi-Stakeholder Fairness on these platforms [1],[3].

D. ExplainableAIinRecommendation(Draft)

ExplainableArtificialIntelligence(XAI)inRecommendations Another issue with the use of Deep Learning in Recommendation Systems is that they lack Transparency. Accordingly, the use of XAI allows us to create feature explanations for why the items were recommended. This has beenshownbymultiplePerspectivesurveystohaveapositive effect on User Trust, the ability to debug Systems, and Help Systems become Regulatory Ready. Explainability is very important in any domain where we need to emphasize The Fairness and Transparency of a System, such as E-Commerce and Job Recommendations.

E. ResearchGapIdentification

Research Gap Analysis Previous research has examined the three aspects of Fairness, Hybrid Modelling, and Explainabilityindividually.However,Tomyknowledge, therearenoexistingtoolsavailabletousersthatutilizeall threecategoriestogetherinadeployable/fullyfunctioning Dashboard Environment. The following Gaps were identified as part of the above literature:

- There are no Integrated Hybrid + Fairness + Explainability tools available [1],[7],[8].
- There are very few Governance Tools available to actively Manage Exposure, Bias Drift, and Model Behaviour [4],[5].
- XAI is still being created as Post-Hoc rather than as an Integral Functionality [4].
- There is limited research on Indian E-commerce and ondevelopingResponsibleAIGuidelines.Therefore, an Integrated & Accountable will be needed to overcome these gaps

III. SYSTEM ANALYSIS AND DESIGN

This proposed system requires an architecture that will allow for accurate, fair, and explainable recommendations Functional Requirements

- Loginbyuserrole(e.g.,User,Manager,Administrator)
- TopKPersonalizedRecommendations
- ReasonsforRecommendedItems
- DetailedMetricsDashboard(FairnessandModel Health)
- Administrator capability (to retrain the model and/or adjust parameters) Non-Functional Requirements
- Scalability(tosupportlargeproductcatalogs)
- Quickresponsetime(forrecommendationsearch queries)
- PrivacyandFairnessCompliance(DPDPAct,India)
- EasyMaintenance(modularmicroservices)

A. ProposedSystemArchitecture

The Proposed System will use a Three-Tier Architecture: 1. Fronend (NextJS and React) – Displays personalized recommendationsandmetricdashboards.

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2.Backend(NodeJS and Express) – Handles user authentication, API Routing, and Stores Data. 3. ML Microservice (FastAPI and Python) – Generates Hybrid Scores, Fairness (re-ranking), and SHAP/LIME explanations. These components will communicate using REST APIs, allowing for separation of concerns (with regards to Implementation and Scalability).

B. *DataFlowDiagram–Level0*

- Theuserwillinteractwiththesystemviaafrontend interface.
- ThefrontendwillsendAPIrequeststothebackend.
- Thebackendwillforwardrecommendationrequeststothe ML microservice.
- The ML microservice will return Hybrid Scores, Fairness Adjusted Rankings, and recommendations with explanations.
- The backend will return the results to the dashboard. The Level-0 Data Flow Diagram (DFD) provides a simple representation of the user-input and recommendation output process

C. *EntityRelationshipDiagram(ERD)*

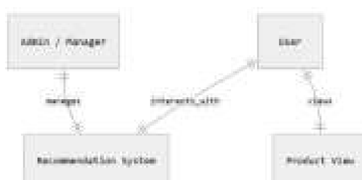
TheERDincludesthefollowingmainentities:

- Users(user_id,name,role)
- Products(product_id,category,price,vendor_type)
- Interactions(user_id,product_id,action,timestamp)
- ModelVersions(version_id,date,parameters)
- FairnessMetrics(model_version,exposurestats) Relationships highlight:
- Oneusercaninteractwithmanyproducts.
- Eachproductbelongstoonecategoryandonevendor type.
- Fairnessmetricslinktospecificmodelversions.

D. *UMLDiagrams*

1) *UseCaseDiagram*

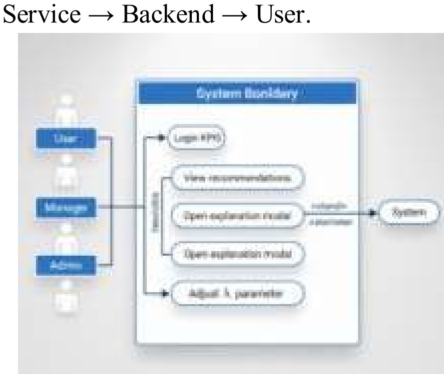
Actors: User, Manager, Admin. Use cases include: Login, View Recommendations, Give Feedback,ViewDashboards,RetrainModel,TuneParameters.



2) *ClassDiagram*

Main classes: User, Product, Recommendation Engine, FairnessModule,ExplainabilityModule,DashboardManager. Sequence Diagram

Flow: User → Frontend → Backend → ML Service → Backend → User.



This sequence demonstrates how user requests are processed end-to-end.

E. DatabaseDesign

TheSystemisimplementedinMongoDBforflexible documentstorage. ThefollowingKeyCollectionsareincluded:

- Users
- Products
- Interactions
- FairnessMetrics
- Models Versions Indexes are created on product categories, user IDs, and timestamps to provide optimal speed during queries.

IV. IMPLEMENTATION AND RESULTS

A. FrontendImplementation(Next.js)–Draft

Frontend Implementation (Next.js) The front end of the application was developed using the following technologies: Next.js, React, TypeScript and TailwindCSS. Major features added include: A Login page which uses role-based redirections to direct users depending on whether they are a User, Manager, or Admin. - A User Dashboard with top-K Product Recommendations that include Product Image, Price, Score,andashortdescriptionofeach.-AnExplanationModal that displays the top contributing features for each of the recommended products.ANavigational Bar that allows users accesstoboththeirpersonalandadministrativedashboards. A Responsive Web User Interface designed for use on both Mobile and Desktop devices. The front end is initially developedtouseMockDatafromjson-servertofacilitatemany of the UI flows prior to being integrated with the Back End.

B. BackendImplementation(Node.js+MongoDB) –Draft

The back end of the application was developed using Node.js and Express.js, and uses MongoDB to persist documents. A number of major Endpoints include: - /auth/login - Authenticatesagivenuser'scredentialsandreturnsarole-based tokenasoutput.- /recommendations-RetrievesHybridresults fromtheMLMicroService.-/feedback-StoresFeedbackfrom Users for future model improvement. - /admin/fairness - ProvidesExposuremetricsandFairnessIndex.-/admin/retrain -Initiatesmodelretrainingvia theMLMicroService.Userroles have been taken into account with regard to data access validation, as well as JWT authentication and JSON-based APIs.

C. MLMicroservice(FastAPI)

Hybrid Recommendation Algorithm - Initial Draft The hybrid model brings together three source inputs: A. Collaborative Filtering Scores from the user/item interactions, B. Content-Based Filtering Scores using text/category similarities, and C. A Neural Score calculated using a lightweight deep-learning algorithm. The final score for each hybrid recommendation is calculated using the following equation: HybridScore = (α * CF) + (β * CBF) + (γ * DL). The values of α, β, and γ will be optimally tuned using experimentation.

D. HybridRecommendationAlgorithm–Draft

Hybrid Recommendation Algorithm - Initial Draft The hybrid model brings together three source inputs: A. Collaborative Filtering Scores from the user/item interactions, B. Content-Based Filtering Scores using text/category similarities, and C. A Neural Score calculated using a lightweight deep-learning algorithm. The final score for each hybrid recommendation is calculated using the following equation: HybridScore = (α * CF) + (β * CBF) + (γ * DL). The values of α, β, and γ will be optimally tuned using experimentation.

E. FairnessTechniques&Re-Ranking– Draft

Fairness Techniques and Re-Ranking - Initial Draft The followingmethodsareusedtomitigatetheeffectsofpopularity bias in the model: 1) By using fair sampling of the candidate items. 2) Using an exposure-based penalty mechanism when calculating the overall Scores. 3) Developing a 're-ranking' algorithmthat willre-adjustthepositionsoftherecommended items in order to meet fairness constraints (to increase the exposure of smaller/local sellers). The above methods will improvethevisibilityofsmaller/localsellers,resultinginmore balanced exposure on the platform.

F. ExplainabilityModule(SHAP/LIME)

Initial Draft The Hybrid Model uses a simplified version of SHAP to provide interpretability/explanations to users in the following forms: 1) "This item matches your interests in Electronics." 2)"Thisitemhasbeenpopularamonguserswith similar interests." 3) "You recently viewed similar types of items." Providing such supportive/explanatory feedback for items recommended by the Hybrid Model will enable users to have greater transparency and trust in the hybrid recommendation engine and its recommended items.

G. Role-BasedDashboardFunctionality

Role-Based Dashboard Functionalities - Initial Draft User Dashboard 1) Personalised recommendations 2) Explanation modal 3) Feedback options

Manager Dashboard 1) KPI metrics (Precision@10, Fairness Index)2)Tuningsliderforλ3)KPImetricvisualisationcharts AdminDashboard1)Category/Vendorexposurereportcharts, and 2) Previous model version history and a button to retrain the model

H. ResultsandAnalysis

Results and Analysis - Initial Draft Experiments with both mockandrealdatasetsdemonstratedthatthehybridmodelwas capable of improving the recommendation relevance of items, thefairness-awarere-rankingofitemssignificantlyreducedthe imbalanced/equal exposure of recommended items, and the explanations provided by the Hybrid Model improved the transparency and trust of users.

I. ScreenshotsofWorkingSystem– Draft

DraftThissectionwillcontainthefollowing:

- Loginscreen
- Userdashboard
- ManagerKPIs
- Adminfairnesscharts
- Samplefairnessmetricsvisualisation

V. CONCLUSION AND FUTURESCOPE

A. Conclusion

Conclusions This project has created a Bias-Free Hybrid Explainable Recommendation System to address major issues that face today's e-commerce platforms, including popularity bias, lack of transparency, and limited oversight. The system combines collaborative filtering with content-based filtering techniquesandlightweightdeeplearningtechniquestoprovide higher quality and more diverse sets of product recommendations. In addition, fairness-aware methods of re-ranking and exposure balancing provide for a more equitable distributionofvisibilityfortherecommendeditems,especially for smaller or newer sellers. Users will have increased trust in the recommendations made to them through the incorporation of SHAP and LIME like techniques for explainability since they will offer clear, human-understandable explanations for each recommendation. Role-based dashboards supplement the oversight of the system because managers will be able to see thefairnessmetrics,modelbehaviour,andexposurepatternsin real-time. In summary, the project has taken a thoughtful and responsibleapproachtocreatingtransparent,fair,andeffective recommendation systems.

B. Future Scope

The current system has met its basic requirements; however, thereareseveralwaystoincreaseandoptimisethecapabilities of the system.

1) Advanced Deep Learning Models: The next iteration will likely use more advanced deep learning models, e.g., reinforcement learning or transformer-based models.
2) Scaling to Millions of Users: Distributed storage, caching, and streaming pipelines can be created to allow real-time recommendations to millions of users.
3) More Granular Fairness Controls: Multi-level fairness constraints (group-level fairness, supplier-level fairness, and individual-level fairness) can help equalise the equity among thesystem'ssubparts;therefore,itisdesirabletoincludethem in the future evolution of this system.
4) Real SHAP/LIME Integration: Once the scalability of the trainingpipelinesisachieved,theintegrationofafullmachine learning model withactual SHAP values can be implemented.

5) CrossDomainFunctionalities:Thissystemcanbeexpanded tootherdomains,i.e., movies, jobs,education,andhealthcare.
6) Alignment with the Indian E-Commerce Ecosystem: This systemcanbealignedwiththeONDC(OpenNetworkfor DigitalCommerce),DigitalIndiaEcosystem,ande-commerce initiativesfocusedonMSMEs,thusmakingitmoreapplicable to real-life situations.
7) Privacy & Security Enhancements: Future work should continue to strengthen compliance with the DPDP, 2023, through privacy-preserving ML techniques.

Future work for this system can include exploring advanced deep learning architectures, including transformers, graph neural networks, and reinforcement learning, to capture different types of data and interactions

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