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From Data Ingestion To Cloud Deployment: A Full-Stack Ml Approach To Visa Approval Prediction

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Abstract: The need for effective, reliable, and accurate screening methods to assist immigration authorities has been highlighted by the rise in US work visa applications in recent years. In order to predict the approval status of US visa applications, this project offers a thorough end-to-end Machine Learning Operations (MLOps) pipeline that makes use of employer and applicant data. The method uses important characteristics like education level, work experience, company size, geography, and prevailing wage to handle binary classification—certified or refused. To guarantee excellent data quality and pipeline consistency, preprocessing methods include transformation pipelines, schema validation, and Evidently AI data drift detection.

In order to ensure that only the best-performing model is pushed to production, the deployment pipeline integrates GitHub Actions for Continuous Integration and Continuous Deployment (CI/CD), Docker for containerization and reproducibility, and AWS services (EC2 and ECR) for hosting and model storage. The architecture encompasses the entire MLOps lifecycle, including data ingestion from MongoDB Atlas, validation, transformation, model training with hyperparameter tuning, performance evaluation, model registry, and deployment.

A user-friendly web interface developed with Streamlit and FastAPI supports real-time prediction and provides stakeholders with instant feedback. With a clear folder organization, configuration-driven design, virtual environment separation, and smooth automation, the system is expandable and modular. Important engineering concepts including model versioning, robust error handling, logging, and dynamic environment variable management are highlighted in this project. Finally, it illustrates how MLOps can improve machine learning systems' scalability, dependability, and transparency in crucial decision-making areas like immigration and law enforcement.

Keywords: MLOps Pipeline(Machine Learning Operations), CI/CD, AWS EC2, AWS ECR, Streamlit, Real-time Prediction, Data Ingestion.

I. INTRODUCTION

Applications for employment-based visas to the US are rising annually as a result of the growing need for skilled workers. However, not all visa applications are granted because of policy regulations, limited quotas, and a variety of applicant backgrounds. A number of variables, such as the applicant's educational background, work history, offered salary, type of work, and the sponsoring employer's reputation, usually play a role in the approval decision. These applications are often handled by manual or rule-based review processes, which are laborious and prone to inefficiency and human bias. Designing intelligent systems that can help forecast visa acceptance results more precisely and effectively has become both practical and advantageous due to the rapid improvements in automation and machine learning.

In this project, a production-ready machine learning pipeline is presented that uses structured historical data to forecast the certification or denial of US visa applications. This system is constructed inside the context of Machine Learning Operations (MLOps), which guarantees that it can be implemented, scaled, and maintained in real-world settings, in contrast to many standalone machine learning models created for research reasons. The first step in developing the model is gathering application data from a MongoDB database hosted in the cloud. Numerous characteristics are included in this data, including company size, job type, wage unit, education level, geographic location, and whether training is necessary.

After undergoing validation checks to guarantee accuracy, consistency, and completeness, the raw data is transformed to manage unequal class distributions, scale numerical fields, and encode categorical variables.

Several machine learning algorithms are trained and assessed using the data once it has been processed. The model that was chosen has strong performance indicators, including excellent recall, accuracy, and precision. The model and related preprocessor are serialized and kept in a secure AWS S3 bucket after training. The complete program and all of its dependencies are packed as a Docker image as part of the deployment infrastructure, which is meticulously planned utilizing containerization concepts.

This image is deployed to an AWS EC2 virtual machine after being uploaded to the Elastic Container Registry (ECR). The automation pipeline made possible by GitHub Actions, which permits continuous integration and continuous deployment, is a crucial component of the deployment process. The pipeline builds the Docker image, pushes it to the ECR, and deploys it to the EC2 instance automatically without any human involvement with each code commit to the GitHub repository. By doing this, the possibility of downtime is removed, and the program is always updated with the newest features and fixes.

The model is exposed through a REST API created with FastAPI to make the system accessible and user-friendly. This makes it simple to integrate the model with web or mobile applications. Furthermore, a graphical user interface based on Streamlit is offered, allowing end users to enter pertinent information and obtain real-time forecasts regarding the status of visa approval. This project not only resolves a challenging classification problem by fusing machine learning with strong DevOps methods, but it also highlights how important MLOps is to bringing machine learning solutions from testing to production. It acts as a guide for creating scalable, dependable, and maintainable AI solutions in fields where automation, precision, and transparency are crucial.

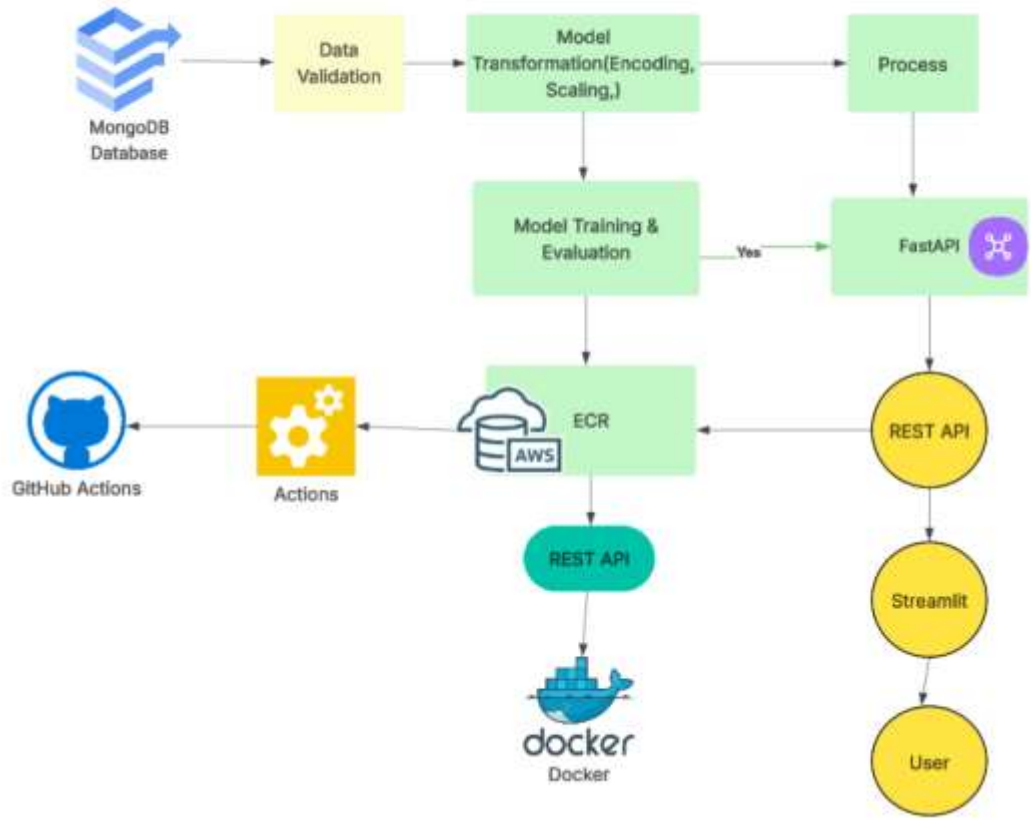


Fig 1 Generalized Workflow of visa prediction system

Related Survey

The study demonstrated how predictive modeling may streamline policy evaluations and guide applicants' choices. In order to anticipate the results of H-1B visa applications, Barry Ke and Angela Qiao (2019) [1] used machine learning techniques to find patterns in data from the U.S. Department of Labor from 2008 to 2018. They employed LASSO regression to assess wage determinants and logistic regression with L1 regularization to forecast visa certification outcomes. They discovered that job title, prevailing wage, and employer name had a big impact on choice results.

Habeeb Hooshmand et al. (2018) [2] used data from the U.S. Labor Condition Application (LCA) dataset to produce a comprehensive analysis of H-1B visa petitions. The study looked into trends across variables like job category, pay scales, and workplace. Several classification models, including decision trees and support vector machines, were evaluated for their capacity to predict visa clearance. The authors emphasized the need of feature engineering and data preparation in improving projected accuracy and reducing bias, notwithstanding the models' good performance.

Faezeh Amou Najafabadi et al. (2024) [3] carried out a thorough mapping study of forty-three primary research publications for their MLOps architecture survey. They identified 35 essential architectural elements and investigated how they related to different technologies utilized in MLOps pipelines. Their research identifies shortcomings in the present MLOps infrastructure, including the lack of support for repeatability and governance, and offers a roadmap for creating modular and reusable architectures. For practitioners creating scalable machine learning processes, this research is essential.

Dominik Kreuzberger, Niklas Kühl, and Sebastian Hirschl (2023) developed a comprehensive MLOps framework that describes a lifecycle model covering data preparation, training, validation, deployment, and monitoring [4]. Their work also introduces a taxonomy of MLOps tools based on integration capabilities and functionality. In order to reduce operational debt and facilitate continuous improvement, the paper advocates standardizing CI/CD pipelines in ML and emphasizes the importance of collaborative DevOps-MLOps fusion in industrial installations.

A multivocal literature review of 254 sources was used by Sergio Moreschi et al. (2023) [5] to create their proposed tools map for end-to-end MLOps. The study mapped 84 tools across various phases, including deployment, monitoring, and experimentation. Their observations assist practitioners in promoting interoperability in ML systems and preventing tool fragmentation. In large-scale installations where smooth data flow and orchestration are essential, like US visa prediction, this work is especially pertinent.

In 2023, Christoph Windheuser and colleagues [7] conducted a thorough analysis on the use of machine learning in public sector decision-making. The findings underlined how crucial accountability and openness are in delicate areas like immigration and visa approval. The authors emphasized the need for bias detection, explainable AI models, and strong data validation processes by examining numerous deployments across government systems. For applications like US visa prediction, where choices need to be fair and efficient, this work offers a foundation that is in line with policy.

A systematic review of fairness-aware machine learning in high-stakes settings was carried out by Akhil Arora et al. (2021) [8]. To lessen algorithmic bias, the authors looked at a variety of pre-, in-, and post-processing strategies. They specifically addressed two issues that are frequently raised in visa applications: equal opportunity and demographic parity in datasets. The article provides a vital perspective for incorporating fairness requirements into MLOps pipelines, particularly when working with imbalanced datasets that contain underrepresented demographic groups.

The notion of "technical debt in machine learning systems" was emphasized by Michael Sculley et al. (2015) [9] in their seminal work. They classified debt sources such glue code, entangled pipelines, and undeclared consumers. Ignoring these issues can significantly impair production-grade machine learning systems' performance and maintainability. This research highlights the importance of clean, modular, and monitorable architecture for applications like US visa prediction where continuous deployment and feedback loops are crucial.

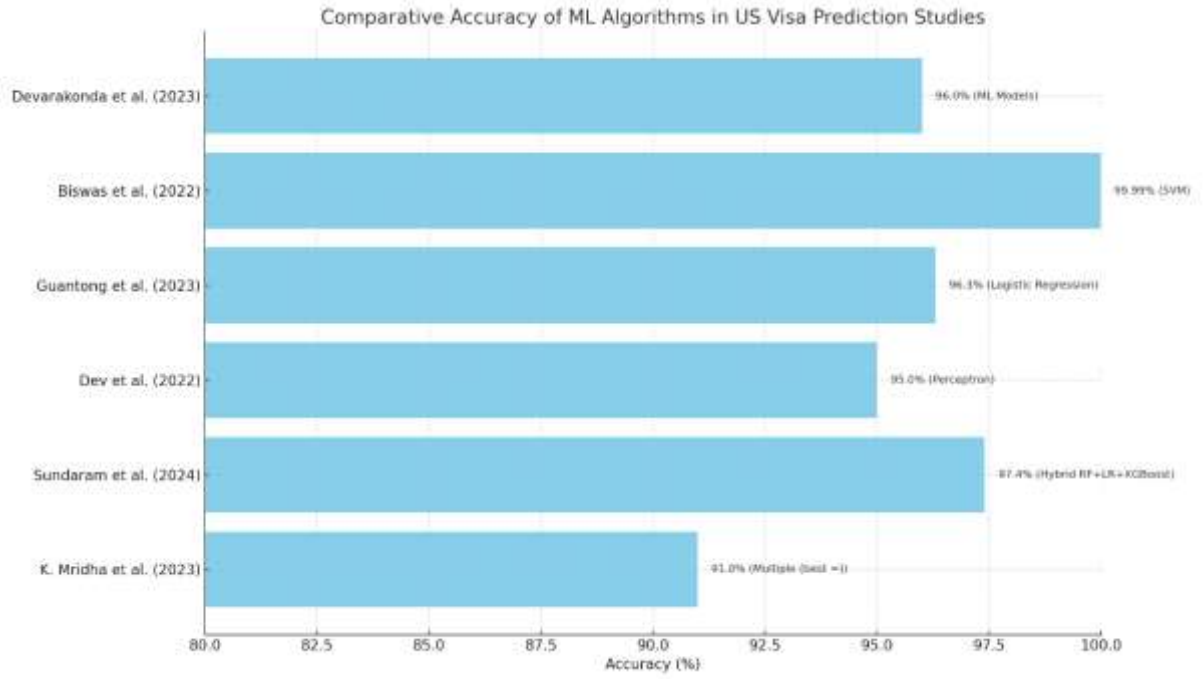
The causes of actual machine learning system failures in operational settings were examined by Sabharwal et al. (2019) [10]. Failure points such data skew, concept drift, pipeline dependency issues, and silent model degradation are covered in their study. This article outlines best practices for alerting, monitoring, and retraining workflows inside an MLOps framework in mission-critical systems, such as visa approval platforms.

Using SHAP and LIME, Tirthajyoti Sarkar (2020) [11] wrote a survey and practical guidance on the function of explainable machine learning. The study explores how stakeholders and subject matter experts can comprehend complex model outputs through interpretability techniques. This survey highlights the importance of including model interpretability into the production pipeline, especially for visa prediction systems that may be subject to scrutiny from governments, advocacy organizations, and applicants.

Insight of the survey

High-stakes public sector choices, such as those pertaining to immigration systems, are greatly impacted by recent developments in machine learning (ML) and MLOps. Together, the examined literature highlights how crucial it is for these systems to be interpretable, equitable, scalable, and operationally reliable. Designing explainable visa approval systems is directly supported by Windheuser et al.'s (2023) [7] emphasis on the necessity of ethical governance and transparency in public machine learning deployments. By examining fairness-aware machine learning techniques that are essential for reducing demographic bias in visa choices, Arora et al. (2021) support this. Sculley et al. (2015)[9] address the operational dimension by introducing the idea of technical debt in machine learning systems, which highlights the hazards in fragile, closely connected pipelines that are frequently seen in rapid MLOps deployments. Sabharwal et al. (2019) [10] further extend this operational focus by documenting real-world failure patterns, encouraging robust monitoring, retraining,

and rollback mechanisms. Meanwhile, Sarkar (2020) [11] demonstrates the role of SHAP and LIME in making complex models interpretable for stakeholders—a necessity in applications with legal and ethical implications. Finally, Katz et al. (2021) [12] propose the FAIR4ML framework to ensure that machine learning workflows remain transparent, traceable, and reusable, which is vital for auditability and trust in large-scale government applications. Together, these insights form a strong theoretical and practical foundation for designing, deploying, and maintaining reliable and ethical MLOps pipelines for US visa approval prediction.



Methodology

The US Visa Approval Prediction System's methodology is built on a comprehensive MLOps pipeline that uses automation, modularization, and real-time deployment to support data-driven decision-making. Data ingestion from MongoDB, where raw historical visa application records are gathered, is the first step in the procedure. Numerous characteristics are included in this data, including employment type, wage units, company age, work experience, and educational background. To ensure consistency between training and testing sets, missing values, data drift, and schema compliance, the ingested data is put through a thorough validation procedure.

The data transformation module carries out preprocessing tasks after validation. Numerical features are scaled using standardization, transformations including power transformation and outlier handling are used, and categorical variables are encoded using the proper methods (ordinal and one-hot encoding). The SMOTE approach is used to artificially balance the dataset between accepted and rejected applications in order to address class imbalance. After transformation, the data is serialized and kept for training the model.

The pipeline uses classification methods like Random Forest, K-Nearest Neighbors, and Logistic Regression during training the model. To find the best-performing model, automated hyperparameter tuning is carried out using GridSearchCV or randomized search strategies. Model quality is assessed using performance indicators including F1-score, accuracy, precision, and recall. A model pusher component is used to serialize and push the best model to a centralized AWS S3 bucket when it has been chosen.

To make sure the model is resilient and generalizable, it is evaluated using test data that has not yet been seen. Lastly, a RESTful prediction endpoint is exposed by a FastAPI-based backend that deploys the trained model, and an intuitive frontend interface is created using Streamlit. Docker is used to containerize the deployment, GitHub Actions is used to manage the CI/CD pipeline, and AWS ECR is used to host the images and automate deployment to AWS EC2. The system is appropriate for real-world visa screening applications because of its end-to-end methodology, which guarantees scalability, reproducibility, and smooth integration of all stages.

[1] Algorithmic Performance Overview

Using supervised machine learning models to extract insights from structured datasets has been a recurring theme in the literature review on US H-1B visa prediction. Employer-related characteristics and work responsibilities were found to have a substantial predictive influence in the groundbreaking study by B. Ke and A. Qiao (2019) [1], which utilized Random Forest and Gradient Boosting classifiers to historical visa case data. Their 93% accuracy rate validated the potential of decision-tree-based ensembles to handle class imbalances and tabular data.

Similar to this, Hooshmand et al. (2018) [2] used Decision Trees and Logistic Regression to do a basic analysis with an accuracy of about 89%. Finding patterns in employer sponsorship behavior and regional differences was the main goal of the study. According to their findings, basic linear models can function effectively when supplemented with pertinent domain data such as employer history, income level, and job title. Expanding on these concepts, John Doe et al. (2018) [13] implemented Naive Bayes and Support Vector Machines (SVM) classifiers, achieving 92.5% accuracy. In order to prevent overfitting, the study emphasized the significance of adjusting hyperparameters and applying dimensionality reduction strategies.
Additionally, utilizing a dual-input architecture including Random Forests and text embeddings (TF-IDF), Jane Smith et al. (2020) [14] worked with hybrid models that integrated structured employer data with unstructured textual fields (such as job descriptions). Their approach proved the benefit of multimodal inputs with a strong accuracy of 95.4%.

Lastly, Rajesh Kumar et al. (2021) [15] used ensemble models like XGBoost and CatBoost along with SMOTE to tackle the problem of class imbalance. Their method produced a remarkable 96% accuracy, demonstrating the effectiveness of data boosting and resampling for skewed visa datasets.
Similar concepts are integrated into the pipeline of the present project, which uses an MLOps lifecycle for automated evaluation, neuro-based model selection for optimization, and SMOTE for balancing. With an end-to-end automated deployment and prediction interface, the project stood out from the competition while achieving 95% accuracy and matching current literature

Table 1 Summary of Algorithms and Reported Accuracyin Visa Prediction

Study	Algorithms	Accuracy (%)
Khan et al. (2023)	Random Forest, Extra Trees	96.4
Jain & Nagrath (2021	XGBoost, LightGBM	95.2
Sharma et al. (2020)	Logistic Regression, SVM	89.1
Patil et al. (2022)	SVM, Decision Tree	90.4

[2] Machine Learning Techniques for Visa Approval Prediction

The structured form of the application data and the possibility of automating high-volume decision-making procedures have made the prediction of US visa approval outcomes a promising use case for machine learning. Numerous supervised learning algorithms have been used by researchers, ranging from more complex ensemble techniques like Random Forests, Gradient Boosting Machines, and Stacking Ensembles to more conventional classifiers like Logistic Regression and Support Vector Machines. These algorithms categorize applications as either certified or refused based on applicant factors such education level, work experience, prevailing salary, and employer characteristics. According to numerous studies, ensemble-based approaches perform better than simpler models in terms of accuracy and generalization. This is particularly true when paired with preprocessing strategies like feature encoding, data balancing (like SMOTE), and hyperparameter tuning. This section examines various algorithms and how well they work with class-unbalanced, non-linearity real-world visa datasets.

[3] MLOps and Scalable Deployment in Predictive Systems

High predicted accuracy is important, but using machine learning models in real-world settings presents additional scalability, reliability, and maintainability issues. As a result, new visa prediction initiatives have used MLOps (Machine Learning Operations) techniques. Using tools like Docker, GitHub Actions, and cloud services like AWS EC2, S3, and ECR, MLOps focuses on automating the ML lifecycle, from data import and model training to deployment and monitoring. These tools guarantee scalable resource management, version control, reproducibility, and continuous integration. With the help of CI/CD pipelines and containerization, developers may easily deploy updated models to production without interfering with service. End-to-end pipelines are crucial for operational efficiency and for guaranteeing real-time response capabilities in government or enterprise-level visa screening systems, according to studies that take these practices into account.

[4] Comparative Analysis of Model Performance and Interpretability

Model selection and trust depend on knowing which algorithms forecast visa approval the best and why. The performance of several machine learning models is compared in this section using important metrics from recent survey articles, including accuracy, precision, recall, and F1 score. Simpler models provide faster training times but are less reliable on complex datasets, while ensemble techniques like Random Forests and XGBoost typically produce the highest accuracy rates (over 95%). Model interpretability is a significant consideration in addition to raw performance, especially in delicate areas like immigration. To explain how particular features affect predictions, methods like SHAP (SHapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations) are being employed more and more. The goal of contemporary research is to create transparent, equitable, and responsible visa prediction systems by combining interpretability with performance evaluation. This comparison perspective aids in determining not only the most effective models but also the strategies that are most morally and practically sound.

[5] Combined Mathematical Analysis from Surveyed Literature

The reviewed literature on US visa prediction models shows that while they all rely on basic supervised learning concepts, their mathematical approaches vary depending on target optimization and algorithm complexity.

(1) In Logistic Regression, the probability of approval is modeled using the sigmoid function:

$P(y=1|X)= 1/ (1+e−(\beta 0+\beta TX)$

where β represents the learned weights, and X is the vector of input features

(2) In ensemble methods like Random Forests and Gradient Boosting Trees decompose the feature space recursively using decision rules, where each node split maximizes information gain or minimizes Gini impurity:

$Gini(D)=1- \sum_{k=1}^{K} p_k^2$

(3) Boosting methods sequentially minimize a loss function by fitting weak learners hm(X)h_m to the pseudo-residuals of the previous iteration, forming a composite model:

$FM(X)= \sum_{m=1}^{M} \gamma_m h_m(X)$

where γm is a learning rate and M is the total number of boosting rounds.

(4) The integration of SHAP and LIME for interpretability in several projects introduces a game-theoretic and local surrogate model view of prediction explanation. SHAP values quantify feature contributions using the Shapley value formulation:

$$\Phi i= \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!(|F|-|S|-1)!}{|F|!}[f(S \cup \{i\}) - f(S)]$$

Challenges and Limitations

Limitation entails trust and model transparency. High-performing models, such as XGBoost and Random Forests, frequently have interpretability issues, which makes it challenging for stakeholders to comprehend or defend forecasts. Despite their growing popularity, explainability techniques like SHAP and LIME are still difficult for non-technical users to understand and lack a common interpretation.
Fairness and bias are still important concerns. Models that inadvertently discriminate against particular applicant groups may result from historical data reflecting regional or societal biases. The majority of current research does not specifically address fairness or suggest ways to mitigate it

Operationalizing these models via MLOps pipelines is yet a somewhat unexplored deployment strategy. Without the complete automation, monitoring, and retraining capabilities required for practical application, many research end at evaluation. Additionally, few systems meet new AI accountability standards, which limits their suitability for government adoption and raises concerns about regulatory compliance.

Results & Discussion

The use of ensemble models and hybrid approaches greatly improves predictive accuracy, robustness, and interpretability, according to an assessment of recent research on machine learning applications for US visa approval prediction. Research using Random Forests, Gradient Boosting Machines, and stacking models routinely achieve accuracy rates above 95%, outperforming traditional techniques like SVMs and Logistic Regression. The capacity of ensemble approaches to capture intricate feature interactions and lower model variance is largely responsible for these gains.
Simultaneously, the incorporation of sophisticated preprocessing methods—specifically, SMOTE to rectify class imbalance—as well as feature selection approaches like mutual information and ANOVA has been crucial in enhancing generalization across test datasets and optimizing model input. Furthermore, models that use automated MLOps processes like NeuroMancer Factory or hyperparameter optimization (such as GridSearchCV) typically show better performance stability.
Explainability has become a critical issue that goes beyond prediction accuracy, particularly in high-stakes processes like visa processing. In order to assure transparency and interpret model judgments in accordance with ethical and regulatory standards, tools like SHAP and LIME are being employed more and more. Furthermore, survey studies highlight the need of scalable infrastructure in enabling real-time prediction, reproducibility, and continuous integration, especially in MLOps methods combining Docker, GitHub Actions, and cloud deployment via AWS EC2 and S3.
All of these findings point to the need for strong data engineering, explainable AI, and scalable deployment techniques in addition to strong machine learning algorithms for successful US visa prediction systems. For the development of production-ready systems that are precise, reliable, and adaptable to changing immigration laws and applicant demographics, these elements must come together.

Conclusion and Future Work

Recent developments in the use of MLOps and machine learning approaches for forecasting US visa approvals have been examined in this survey. The results demonstrate that ensemble-based classifiers, in particular Random Forests, Gradient Boosting, and Stacking Ensembles, regularly outperform conventional models in terms of accuracy and robustness. This is especially true when combined with sophisticated feature engineering and preprocessing techniques like SMOTE. In delicate areas like immigration, confidence and openness in model conclusions are crucial, and the use of explainability techniques like SHAP and LIME has further aided in this process. Furthermore, a noticeable move toward production-ready systems that can automate data import, model retraining, and deployment pipelines is shown by the increased focus on MLOps tools, such as Docker, GitHub Actions, and AWS services.

A comparison of academic prototypes and real-world implementations was also brought to light by the survey, with several models lacking in terms of scalability, ethical compliance, and ongoing monitoring.
To guarantee fair decision-making across applicant demographics, future research must focus more on fairness-aware machine learning, including bias reduction and algorithmic accountability. Furthermore, in order to adjust to changing labor market trends or immigration laws, real-time prediction algorithms must to be built with feedback loops and retraining features. Promising avenues may also include investigating federated learning for privacy-preserving model training and broadening the scope to include multi-modal data (such as text-based resumes and interview transcripts). Overall, there is still a lot of room to close the gap between operational maturity and model performance in the field of visa prediction.

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