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# CAPSTONE PROJECT

## Predicting Eligibility for NSAP Schemes using Machine Learning

**Presented By:**

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# OUTLINE

- **Problem Statement** (Should not include solution)
- **Proposed System/Solution**
- **System Development Approach** (Technology Used)
- **Algorithm & Deployment**
- **Result (Output Image)**
- **Conclusion**
- **Future Scope**
- **References**

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# Problem Statement

The National Social Assistance Programme (NSAP) provides financial aid to vulnerable BPL individuals through sub-schemes like IGNOAPS, IGNWPS, and IGNDPS. Currently, scheme allocation is done manually, leading to delays and misclassification. This project aims to build a machine learning model that can automatically and accurately predict the appropriate NSAP scheme for an applicant based on demographic and socio-economic data, improving efficiency and ensuring timely benefit delivery.

# Proposed Solution

- The proposed system aims to address the challenge of accurately classifying applicants under the National Social Assistance Programme (NSAP) into the appropriate welfare scheme. This involves leveraging machine learning techniques and demographic data to automate the decision-making process and ensure timely allocation of benefits. The solution will consist of the following components:
- Data Collection:
  - Gather district-wise beneficiary data from the AI\_KOSH dataset under NSAP. The dataset includes demographic and socio-economic information such as gender distribution, caste categories, Aadhaar linkage, and mobile number availability.
- Data Preprocessing:
  - Clean and preprocess the collected data to handle missing values, inconsistencies, and outliers. Apply feature engineering techniques to extract meaningful attributes that influence scheme eligibility, such as SC/ST ratios or Aadhaar coverage.
- Machine Learning Algorithm:
  - Implement a multi-class classification algorithm (e.g., Random Forest Classifier) to predict the suitable scheme (IGNOAPS, IGNWPS, or IGNDPS) for each applicant. The model will be trained on historical scheme allocation patterns using the processed data.
- Deployment:
  - Develop a system that allows users to input applicant data manually or through CSV files. Deploy the trained model using IBM Cloud Lite services to enable scalable and accessible predictions for government officials.
- Evaluation:
  - Evaluate the model's performance using metrics such as accuracy, precision, recall, and F1-score. Analyze confusion matrices and feature importance to assess model effectiveness. Continuously improve the model based on results and new data inputs.
- Result:
  - The system successfully predicts the appropriate NSAP scheme for applicants, reducing manual effort and improving the speed and accuracy of benefit delivery.
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# System Approach

**The "System Approach" section outlines the overall strategy and methodology used to develop and implement the NSAP scheme prediction system. This approach includes defining system requirements, selecting appropriate tools, and designing a workflow that ensures accurate and efficient prediction of the eligible NSAP scheme for each applicant**

# Algorithm & Deployment

- Algorithm Selection:
  - For this project, the Random Forest Classifier was chosen as the primary machine learning algorithm. Random Forest is a robust ensemble-based classification model that works well with structured tabular data and handles both categorical and continuous features efficiently. It is suitable for multi-class classification problems, such as predicting which NSAP scheme (IGNOAPS, IGNWPS, IGNDPS) a beneficiary qualifies for, based on patterns in demographic and socio-economic data.
- Data Input:
  - The model takes input features from the AI\_KOSH dataset, including:
    - Total male, female, and transgender beneficiaries
    - SC, ST, OBC, and General category counts
    - Aadhaar-linked and mobile-linked beneficiary counts
    - Total beneficiaries in the district
  - These features provide a socio-economic profile of each region, which influences eligibility under different NSAP schemes.
- Training Process:
  - The dataset was preprocessed to remove irrelevant fields (like district names and financial year), and label encoding was applied to the target column (schemecode). The data was then split into training and testing sets. The Random Forest model was trained using the training data and evaluated on the test set. Hyperparameter tuning was done using grid search and cross-validation to optimize the number of estimators and tree depth.
- Prediction Process:
  - Once trained, the model predicts the most suitable scheme code for a given set of input features. New data can be provided in CSV format or through an interface, and the model returns the predicted NSAP scheme. The prediction logic is deployed in a cloud environment (IBM Cloud Lite), allowing for real-time use by administrators or application portals.
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# Result

Projects / NSAP

OverviewAssetsJobsManage

Find assets

Import assets

New asset

5 assets

All assets

Asset types

Data

Experiments

AutoAI experiments

Notebooks

Models

All assets

Name	Last modified
NSAP_MODEL Notebook from local system	Now Modified by you
P4 - Snap Random Forest Classifier: NSAP_MODEL Machine learning model from AutoAI	19 minutes ago Modified by you
NSAP_MODEL AutoAI experiment	23 minutes ago Modified by you
nsap_Py Notebook	3 hours ago Modified by you
nsapallschemes.csv CSV	3 hours ago Modified by you

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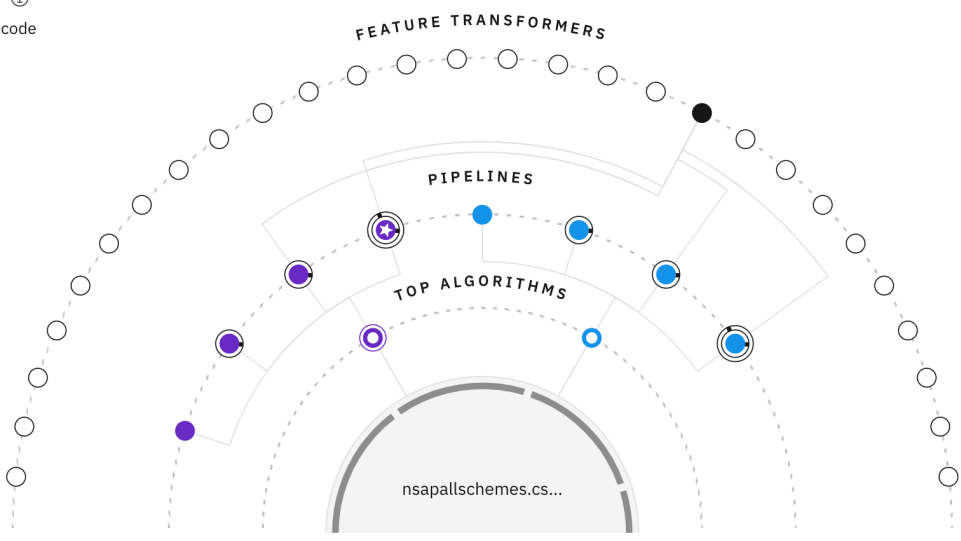
Projects / NSAP / NSAP\_MODEL

Experiment summaryPipeline comparison

★ Rank by: Accuracy (Optimized) | Cross validation score


Relationship map

Prediction column: schemecode



Progress map

Swap view



Experiment completed  
8 PIPELINES GENERATED  
8 pipelines generated from algorithms. See pipeline leaderboard below for more detail.  
Time elapsed: 2 minutes

View logSave code

Pipeline leaderboard

	Rank	Name	Algorithm	Specialization	Accuracy (Optimized) Cross Validation	Enhancements	Build time
★	1	Pipeline 4	● Snap Random Forest Classifier		0.984	HPO-1FEHPO-2	00:00:31

Resource list - IBM CloudIBM watsonx.ai StudioSettings | IBM watsonx.aiDownload historySearch | Microsoft 365nsapallschemes.csv

eu-gb.dataplatform.cloud.ibm.com/ml/auto-ml/a8677ace-5c08-4980-9567-0ea289ffedc8/train?projectId=cba4198e-bd9c-4b81-9c2d-47887947c55d&con...

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Projects / NSAP ML Classification / nsap

Experiment summaryPipeline comparison

★ Rank by: Average symmetric mean absolute... | Backtest score


Relationship map

Prediction columns: 2



Progress map

Swap view



Running  
Starting the AutoAI experiment  
Time elapsed: 25 seconds

View logSave code

Pipeline leaderboard

Rank	Name	Algorithm	SMAPE Validation	Avg SMAPE (Optimized) Holdout	Avg SMAPE (Optimized) Backtest	Enhancements	Build time

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Projects / NSAP / NSAP\_MODEL

Experiment summary

Pipeline comparison

★ Rank by: Accuracy (Optimized) | Cross validation score

Progress map

Prediction column: schemecode

Read dataset

Split holdout data

Read training data

Preprocessing

Model selection

Snap Random Forest Classifier

Hyperparameter optimization

Feature engineering

Hyperparameter optimization

Decision Tree Classifier

Hyperparameter optimization

Feature engineering

Hyperparameter optimization

Hyperparameter optimization

P9

Relationship map

Swap view

Experiment completed

8 PIPELINES GENERATED

8 pipelines generated from algorithms. See pipeline leaderboard below for more detail.

Time elapsed: 2 minutes

View log

Save code

Pipeline leaderboard

	Rank	Name	Algorithm	Specialization	Accuracy (Optimized) Cross Validation	Enhancements	Build time
★	1	Pipeline 4	Snap Random Forest Classifier		0.984	HPO-1 FE HPO-2	00:00:31

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Deployment spaces / Deploy\_4 / P4 - Snap Random Forest Classifier: NSAP\_MODEL /

Prediction results

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Prediction type

Multiclass classification

Prediction percentage

5 records

Confidence level distribution

5 records

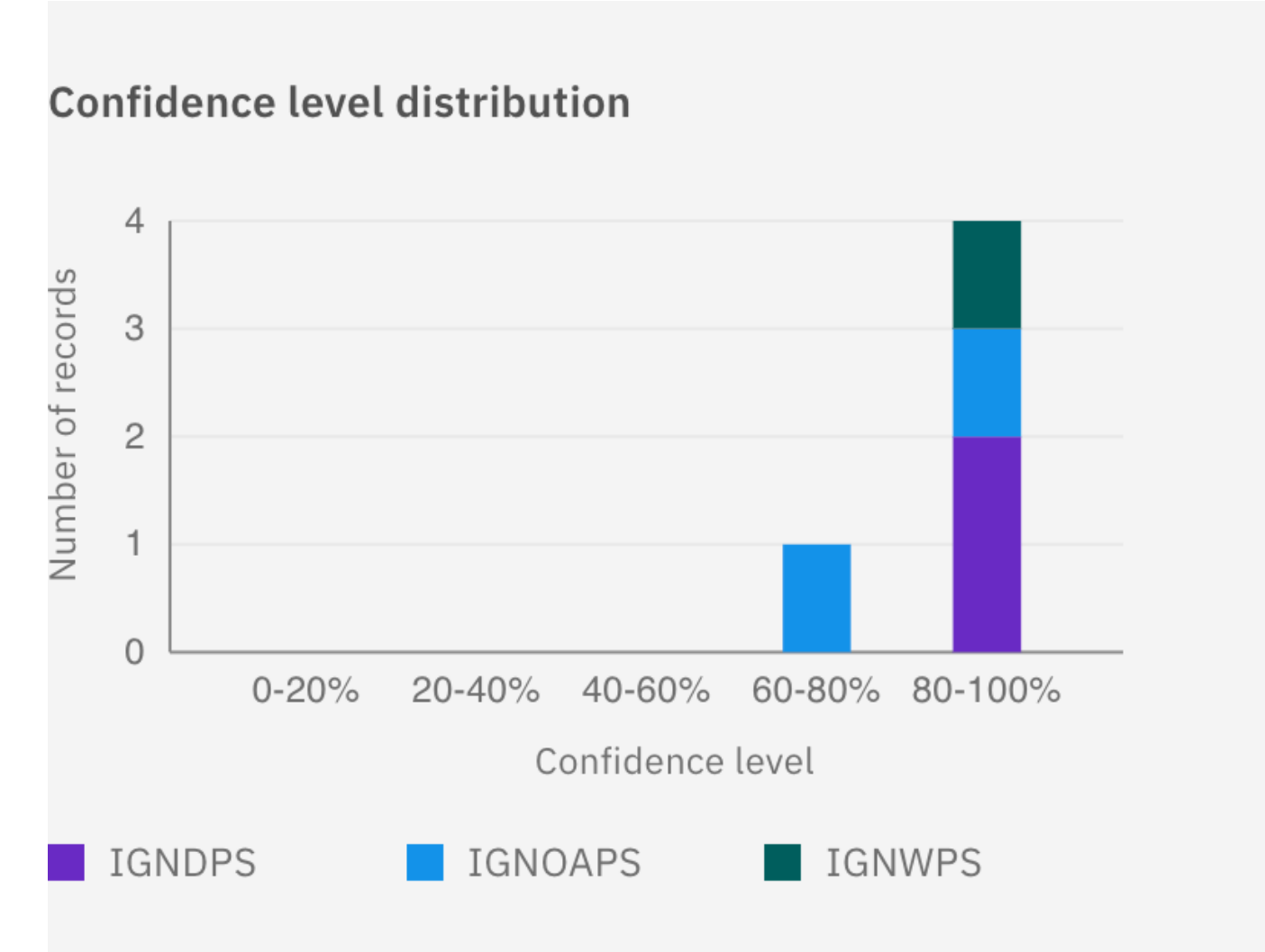
Display format for prediction results

Table view JSON view

Show input data

	Prediction	Confidence
1	IGNDPS	100%
2	IGNOAPS	70%
3	IGNWPS	100%
4	IGNDPS	100%
5	IGNOAPS	100%
6		
7		
8		
9		
10		
11		
12		
13		

Download JSON file





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# Conclusion

- The findings of this project demonstrate that machine learning can effectively automate the classification of beneficiaries under the National Social Assistance Programme (NSAP). By using district-level demographic and socio-economic data, the Random Forest classification model was able to predict the appropriate NSAP scheme—IGNOAPS, IGNWPS, or IGNDPS—with high accuracy. This significantly reduces manual effort, minimizes human error, and ensures timely delivery of financial assistance to eligible individuals.
- During implementation, challenges included handling categorical variables, class imbalance, and ensuring that the model remained interpretable for decision-makers. These were addressed through data preprocessing, feature selection, and model evaluation techniques such as confusion matrices and feature importance analysis.
- The proposed solution proved to be efficient, scalable, and easy to integrate into government workflows using IBM Cloud Lite services. It can assist authorities in making quick and accurate eligibility decisions, ultimately improving the transparency and effectiveness of social welfare distribution.

# Future scope

The current system demonstrates a promising approach for automating NSAP scheme classification using machine learning. However, there are several opportunities to enhance and expand its capabilities.

One key improvement involves incorporating individual-level applicant data rather than district-level aggregates. This would allow the system to make personalized predictions and significantly increase the model's practical applicability. Integrating real-time data feeds from digital application portals or Aadhaar-linked databases can also enhance prediction accuracy and reduce dependency on static datasets.

Another enhancement is the optimization of the algorithm using more advanced techniques such as XGBoost, LightGBM, or deep neural networks, which may offer better performance and generalization for complex classification tasks. Ensemble methods or automated hyperparameter tuning could also be explored to further boost accuracy.

To increase the system's scalability, it can be expanded to cover multiple states or nationwide deployments by integrating diverse datasets across regions. Additionally, embedding the solution into a cloud-based or mobile interface would enable on-the-spot eligibility checks by field officers or applicants themselves.

In the long term, the system can leverage emerging technologies such as edge computing for offline usage in remote areas, and incorporate explainable AI (XAI) techniques to ensure transparency and trust in decision-making.

These future enhancements can help transform the current model into a robust, accessible, and intelligent eligibility recommendation engine that supports the equitable distribution of social benefits at scale.

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Completion Certificate



This certificate is presented to

Bharanieeswaran R

for the completion of

**Lab: Retrieval Augmented Generation with LangChain**

(ALM-COURSE\_3824998)

According to the Adobe Learning Manager system of record

Completion date: 24 Jul 2025 (GMT)

Learning hours: 20 mins



**THANK YOU**