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Application of machine learning to assess people's perception of household energy in the developing world: A case of Nepal

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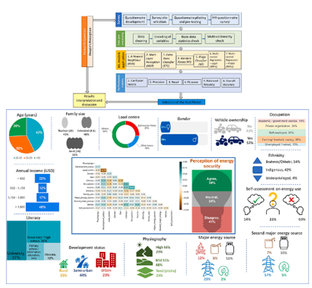
HIGHLIGHTS

- Data driven ML models are better in classifying people's energy perceptions.
- Economy and lack of awareness contribute most to resist energy behaviour changes.
- Fuel-stacking is prevalent due to distrust in the state.
- Grass-root level responses have strong policy implications.

GRAPHICAL ABSTRACT



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ABSTRACT

Research on social aspects of energy and those applying machine learning (ML) is limited compared to the 'hard' disciplines such as science and engineering. We aim to contribute to this niche through this multidisciplinary study integrating energy, social science and ML. Specifically, we aim: (i) to compare the applicability of different ML models in household (HH) energy; and (ii) to explain people's perception of HH energy using the most appropriate model. We carried out cross-sectional survey of 323 HHs in a developing country (Nepal) and extracted 14 predictor variables and one response variable. We tested the performance of seven ML models: *K-Nearest Neighbors (KNN), Multi-Layer Perceptron (MLP), Extra Trees Classifier (ETC), Random Forest (RF), Ridge Classifier (RC), Multinomial Regression–Logit (MR-L)* and *Probit (MR-P)* in classifying people's responses. The models were evaluated against six metrics (*confusion matrix, precision, f1 score, recall, balanced accuracy* and *overall accuracy*). In this study, *ETC* outperformed all other models demonstrating a *balanced accuracy* of 0.79, 0.95 and 0.68 respectively for the *Agree, Neutral* and *Disagree* response categories. Results showed that, compared to conventional statistical models, data driven ML models are better in classifying people's perceptions. It was seen that the majority of the surveyed people from rural (68%) and semi-urban areas (67%) tend to resist energy changes due to economic constraints and lack of awareness. Interestingly, most (73%) of the urban residents are open to changes, but still resort to fuel-stacking because of distrust in the state. These grass-root level responses have strong policy implications.

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1. Introduction

Scholars have recommended against "assuming" social behaviour, particularly related to perception and adoption of new technologies, because of the highly uncertain dynamics between different dimensions of the society [1,2]. The energy sector, in particular, impacts multiple disciplines and operates on various scales, ranging from households to national and regional levels [3–6]. Furthermore, energy is both a building block of the nation as well as a gauge to measure its development [7,8].

Studies have explored different social aspects of energy. For instance, Conradie et al. [9] examined people's behaviour regarding space heating in Europe while Braito et al. [10] assessed photovoltaic investment in Austria and Italy. Similarly, adoption of renewable energy technologies at the household (HH) scale in Germany was studied by Jacksohn et al. [11] and six Mediterranean countries by Strazzera and Statzu [12]. Tekler et al. [13] presented a case study of acceptance of better energy technologies in the workplace in Singapore. Tsvetanov [14] showed that inappropriate policies might actually hinder solar PV penetration rather than encouraging it, taking the case of US. Additionally, studies highlight the importance of awareness, information dissemination [15], and policy reforms [16] in promoting sustainable energy practices. However, distinct global north-south disparities are evident. The developed regions have higher economic and technological resource base [9,17,18], greater awareness [19–21], access to efficient appliances [22,23], and investments in research and development [24,25]. Moreover, Ren and Sovacool [26] show that energy research in the global north is mainly focused on problems facing the industrialized world where there is abundance of research funds.

Contrarily, developing countries suffer from impacts of poverty [27,28], political instabilities [29,30], weak governance [31,32], corruption [33,34], and low literacy rates [35,36]. That is why, these nations are massively reliant on traditional/conventional (mostly fossil and biomass) fuels in their generation mix while using energy inefficient appliances [37]. Furthermore, vulnerabilities associated with energy technologies, such as storage type hydropower, also play a huge role in their adoption in the developing region [38]. The energy choices people are provided by the state are limited [39,40,41]. Therefore, chances of transitioning to cleaner and more efficient energy technologies are rather lean despite willingness and efforts [42–44]. Moreover, Sovacool [45] and Sovacool et al. [46] highlighted that 'hard' disciplines such as economics, statistics, physics, mathematics and engineering have outcasted social and behavioural sciences in energy research. Hence, comprehending people's voices from bottom-up is necessary for policy making, planning and implementation, particularly in the developing world [47]. Catering to the social aspects of energy research in a developing country is a key contribution of this study.

Modelling social behaviour with econometric models is common among researchers. The popularly used models include linear regression and logistic regression (for example, *logit, probit* variants) with binomial/multinomial types. These models have found application across different disciplines mainly to understand people's perceptions and behaviour such as in agriculture [48]; food security [49,50]; livestock [51]; health [52,53]; climate change [54,55]; disasters [56,57]; and energy [58,59], among others. Researchers typically select a set of independent variables, based on literature review, informant interviews and expert judgement, and regress them against dependent variables [60]. Such models generally assume a linear relationship between predictor and dependent variables [61] and/or are usually based on assumptions of no multicollinearity, no heteroskedasticity, normal distribution of error terms and no omitted variable bias [60,62–66], which may not always hold true. Whenever people's behaviours are influenced by an interplay of intertwined societal factors [67–69], non-linearities become more prominent. While the conventional statistical models have been successful in explaining such behaviours to some extent, their representations might turn out to be inapt. This is where application of data driven machine learning (ML) methods can be more efficient. Our contribution lies in targeting this niche, taking the case of a South Asian developing country - Nepal. We test the performance of seven ML models using multiple evaluation metrics to arrive at a rational choice of the 'best' model for the social context of the study region.

Hence, this study carries twin objectives and is aimed at understanding people's perception of energy at the HH level of Nepal using a ML approach. Specifically, this study aims:

1 To evaluate the applicability of ML modelling to understand energy related concerns at the HH level using primary data
2 To analyze and explain people's perception of the adequacy of the current energy generation technologies and HH consumption practices using the most appropriate ML model

2. Machine learning modelling of socio-economic interrelationships

Studies show that level of education, awareness and tendency towards positive change are generally expected to be positively and linearly related [70–72]. In addition, people living in the economically better-off urban areas are expected to be willing to adopt new fuels and energy efficient technologies [73–76]. However, studies in Nepal have shown that people from the rural and urban areas alike are habituated to the existing fuels, they feel safe (in terms of energy security) in continuing the use of current fuels and also have a myopic impression that newer technologies are expensive [29,59]. When these types of non-linearities arise, prediction or classification of people's perceptions and behaviour becomes a challenging task.

Data driven machine learning (ML) methods can be more efficient in explaining social responses compared to conventional statistical models. A distinct difference between these two types of models is that the former is concentrated on predictive accuracy and controlling overfitting leveraging the flexibility of data and model structures to explain problems more efficiently while the latter focus on statistical properties of estimators for hypothesis testing [60]. Moreover, supervised/unsupervised ML models have gained popularity due to advancements in computational capabilities and easy access to software/codes [77,78]. Hence, researchers have visualized ML as an applied econometric approach [79].

As a result, there has been considerable research in ML methods applied to agriculture [80,81], healthcare [78,82], economics [60], education [83], materials science [66], construction [84], energy [37,85–87], natural disasters [88], among many others disciplines. Furthermore, studies such as Storm et al. [60], Benos et al. [77], Liakos et al. [89], Shaik et al. [78] and Meshram et al. [90] provide extensive review of the applicability of ML models to various sectors of the society However, application of ML models in energy has mostly been concentrated in electricity and power sectors [91–95] and energy storage and conversion technologies [87,96–98]. Studies modelling social side of energy has not got much attention compared to the other areas. Furthermore, different types of ML models such as non-parametric and instance-based, neural networks, tree-based, and linear, among others are more versatile in handling various types of observed data (binary, categorical, continuous, ordinal, etc.) and do not require strict assumptions of normality or those of conventional statistical models [61]. However, selecting the best ML model for a given dataset is a challenge which we aim to address through this research by implementing a robust evaluation approach.

3. Study area

Nepal is a landlocked mountainous country in South Asia situated between India and China (Fig. 1). The country can be divided broadly into four physiographic regions, namely, mountains, high hills, mid-hills and Terai plains. Nepal's total energy consumption amounted to 14.9million tons of oil equivalent (toe) in the fiscal year 2020/2021

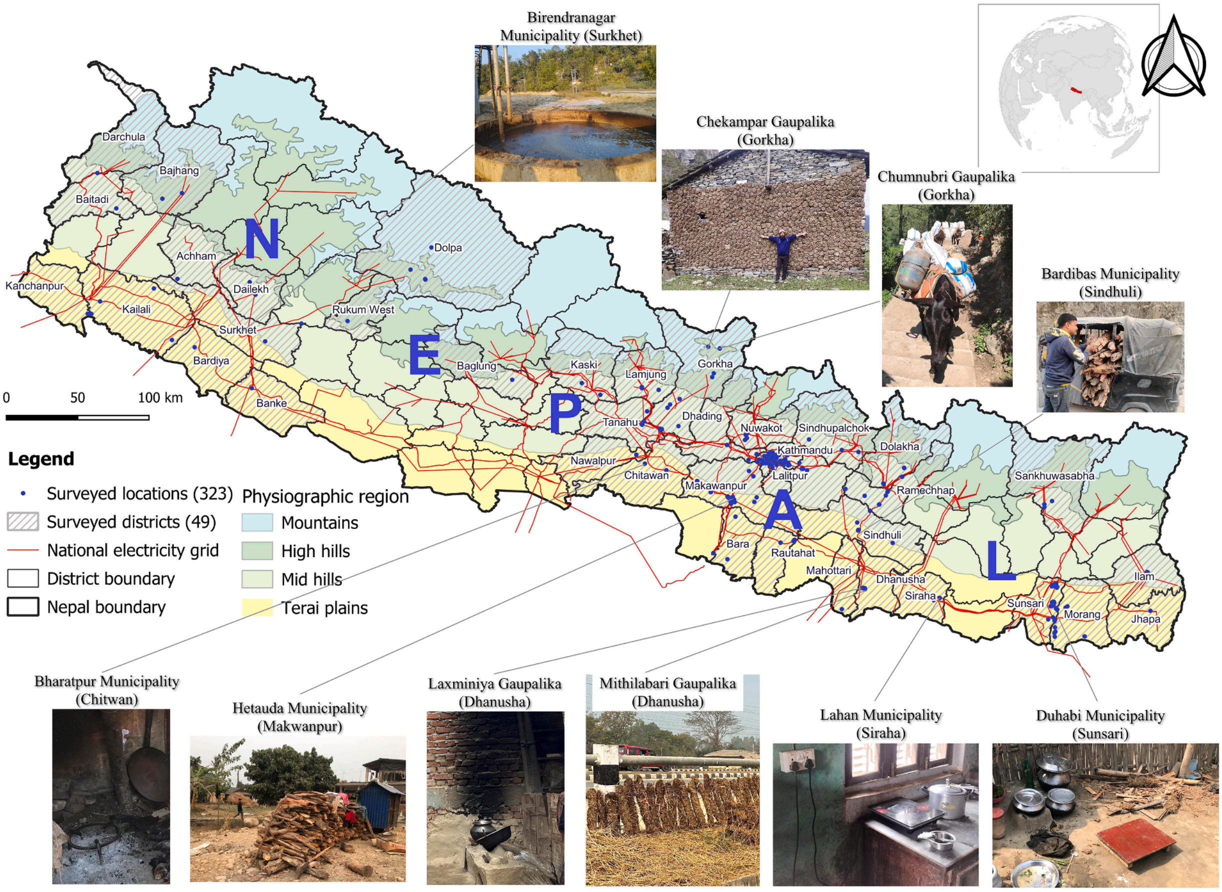

Fig. 1. Location map of Nepal with surveyed points along with districts (in parentheses) and peculiar fuels used for household use. Photos from field team: community biogas plant in Surkhet and 2,000W electric cooktop in a rural house in Siraha (PC: Nawaraj Sanjel); circular shaped 'guitha' sun dried on walls in Gorkha (Nabraj Dhakal); firewood being transported in an auto rickshaw in Sindhuli (Ashish Chapagain); three-legged iron stove for burning firewood in Chitwan and firewood being sundried at a yard in Makwanpur (Insaf Aryal); dung sun dried on footpath and mud stoves for burning them in Dhanusha and Sunsari, and mule carrying LPG cylinder on its back in a remote village of Gorkha (Bipin Dahal).

[99]. The energy generation mix is comprised of three sources: traditional (firewood, agricultural residue, and dry dung used for direct combustion), commercial (petroleum, coal, and grid electricity from large and medium hydropower projects), and other off-grid renewables (micro-hydropower, solar and biogass). In 2020/2021, traditional sources had the largest contribution (65%) to the energy mix , while commercial sources had 32% and renewables had 3% [99]. As for electricity generation, the national grid of Nepal was connected to a total of 2205 MW, generated cumulatively by the government, private sector, and imports and the total annual electricity consumption was 10,686 GWh [100]. The total length of transmission lines in Nepal at the end of 2021/22 was 5329 circuit km (3,816 km of 132 kV; 897 km of 220 kV; 514 km of 66 kV and 102 km of 400 kV) [100]. Most of the electricity generation (92%) comes from large hydroelectric projects, with only 2.2% from solar, 2.3% from thermal, and 3.5% from other smaller renewable energy sources [99].

4. Methodology

We adopted a mixed-method approach in this multi-disciplinary study (Fig. 2). It consisted of six stages: household survey, data pre-processing, application of seven ML models, evaluation of the models based on six performance metrics, and selection of the best model. The final step consisted of examining people's perception of the domestic energy sector of Nepal by analyzing the socio-economic characteristics of the study area based on the feature importance obtained from the best-fit model.

4.1. Household survey

We conducted a cross-sectional survey in Nepal, gathering data from 350 households. Questionnaires were developed in order to collect information on the explanatory variables based on extensive literature [9–12,14–16,18–23,29,34,38,39,41,101–108]. The questionnaire was shared with nine experts (academicians, government officials and energy practitioners) who are well acquainted with the energy sector of Nepal. Based on their suggestions, it was refined and pre-tested at five HHs before the survey rollout. The in-person HH questionnaire surveys were administered from December 2022 to February 2023 using a random sampling approach. Trained interviewers conducted the interviews at the participant's home strictly following ethical requirements of clearance *HREC ID H22REA258* issued by the Human Research Ethics Committee, University of Southern Queensland, Australia. Respondents were chosen in such a way that they were knowledgeable about the energy related concerns in their HHs. HH heads were preferable, however, in many cases it was found that the younger members of the family were more aware of and had a better say in energy related decisions in their houses. Koirala and Acharya [59] even suggest a possibility that elderly people might be scared to try new technologies in Nepal.

It is important that the sampled households are representative of a number of attributes pertaining to our research objectives. Therefore, diversity in the use of energy was the major criteria for survey site selection. This was further governed by whether a house was electrified or non-electrified. Use of grid electricity is the proxy variable to identify

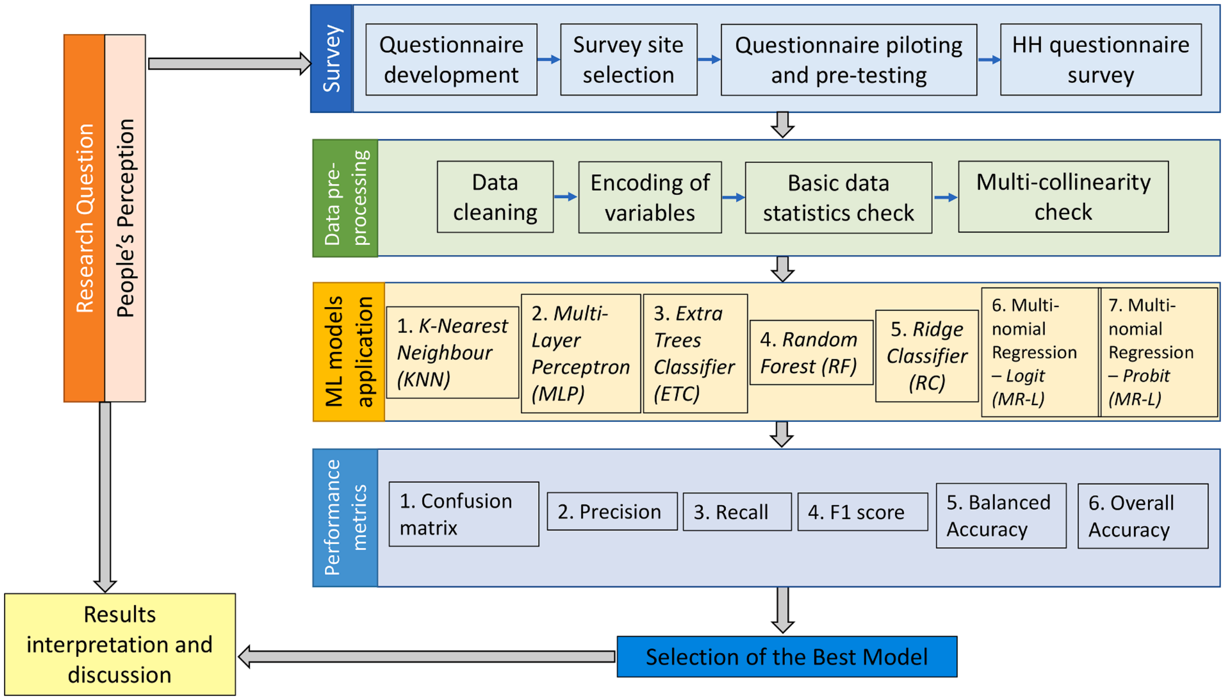

Fig. 2. Overall research methodology of this study; ML – machine learning.

the electrification condition. Additionally, urban, rural and semi-urban areas have different energy consumption patterns in Nepal. Hence, this was chosen as another important deciding factor for survey site selection. Moreover, physiographical region and load centres are two variables which indicate the remoteness of a location. In addition, diverse energy (mainly electricity) generation technologies are prevalent in Nepal. Hence, this criteria of including as many such technologies as possible was adopted during site selection. Locations were fixed such that information from the residents of industrial areas, major hydropower projects (currently under operation and planned), representative micro-hydropower projects and solar projects were obtained during the survey. The survey site selection criteria adopted in this study has been presented in Annex Table A1.

A considerable homogeneity can be seen in the energy consumption pattern and social settings across villages throughout the country. Similarly, the energy scenario is very much similar across the urban areas (cities and towns). Likewise, homogeneity within and diversity across the classes of *physiography* (high hills, mid hills and terai plains), *family size* (nuclear, extended and join), *gender* (female and male), age (20-35, 35-50, >50), *literacy* (illiterate, primary school/informal education, secondary/high school, university), *load centres* (Kathmandu city, other towns, others), *major sources of energy* (grid electricity, LPG, petroleum and renewables), *annual HH income* (< USD 692, 692 – 1,154, 1,154 – 1,960 and >1,960) and *primary occupation* (academic/government service, farming/livestock rearing, private organization, self-employed and unemployed/retired) was maintained by the sample size. Therefore, based on the homogeneity of the sample clusters, the sample size utilized in this study is deemed adequate. Furthermore, it has been made sure that a minimum sample size of 30 has been maintained for each cluster, ensuring a robust representation for analysis and representation (Annex Table A1 and Annex Table B1).

4.2. Data pre-processing

Out of the 350 HH survey responses, 27 were excluded because they were either incomplete, irrelevant or not specific, leading to a final sample size of 323. A total of 14 independent (predictor) variables and one response variable were selected to answer our research question of people's perception of energy availability and consumption at the HH level. The predictor variables were of mixed type including continuous, binary and categorical data. The predictor variables were categorized into different classes; justification for the classification is presented in Annex Table B1. As discussed earlier, homogeneity within and diversity across the classes of each predictor variable was key to our classification. Furthermore, the response variable was one hot encoded to make it multilabel in order to estimate the contributions of the individual predictor variable on each label. After encoding, the basic statistics of the observed data, spread of each predictor variable in the different classes and multi-collinearity were checked (Fig. 3).

4.3. Application of machine learning models

Our dataset consisted of multiple types of variables. Based on the multilabel classification of the response variable, we chose seven ML models (Table 1) capable of handling multiple categorical data for our study. A brief description of each model is given in the table while the details of the models are provided in Annex C. These models were implemented in *python* using *sklearn, imblearn, statsmodels* in addition to *pandas, numpy, scipy, matplotlib* and *seaborn* libraries.

4.4. Performance metrics

Different types of performance metrics are useful for evaluating and comparing the effectiveness of a classification algorithm. We have adopted six metrics (*confusion matrix, accuracy, balanced accuracy, precision, recall*, and *f1 score*) in this study. Details of these metrics are provided in Table 2. Using these performance metrics, we carried our cross-validation for all the models to assess how well they perform on datasets for which they have not been trained. We performed runs for four simulations by varying the training-testing data split taking 80:20, 70:30, 60:40 and 50:50 values to evaluate the robustness of all the models. This approach ensures that the model results are well-validated and can be confidently used for feature selection.

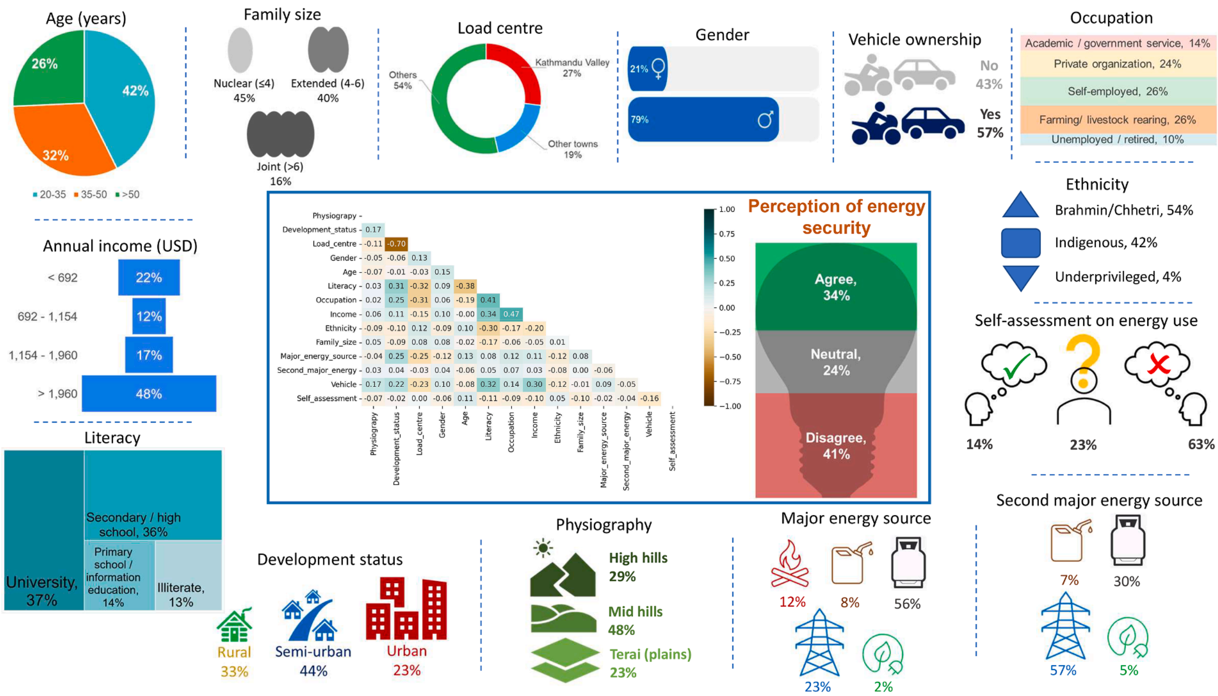

Fig. 3. Spread of data from the sampled households across the different classes of explanatory and response variables. Please refer to Annex B for the categorization of the explanatory variables.

4.5. *Selection of the best model*

Models may demonstrate varying performances in terms of the metrics discussed above. However, an effective model will exhibit high *precision, recall, f1 score, balanced accuracy, overall accuracy*, and show a desirable *confusion matrix* with well-distributed results. Hence, we adopted a robust methodology for best model selection in this study and assessed the performance of each ML model using six metrics (Table 2). Finally, we selected the model that consistently performed well across all evaluation metrics.

The feature importance derived from the best performing model provides information on the relative importance of the explanatory variables on the response variable. Since we have used a multi-label classification of the dependent variable, the feature importance of each variable on each label was extracted and analysed separately. This led to a comprehension of the segregated impacts of each explanatory variable on each response class which was useful in explaining people's perception. Key policy aspects relating to the people's perception of HH energy were also discussed inducing evidence-based policy implications.

5. Results

5.1. *Survey data summary*

There are 14 descriptive variables considered in this study. Among them, 'Age', 'Family size', 'Load centre', 'Vehicle ownership', 'Occupation', 'Annual income', 'Literacy', 'Development status' and 'Physiography' were found balanced across the different classes (Fig. 3). This indicates that our sample size and the ML classification strategy adopted are less likely to give biased results. There is an imbalance in some variables such as 'Gender' and 'Ethnicity' which is expected because of the social context in Nepal. Likewise, a very small number of the people reported using renewable energy as their major and/or second major source of HH energy. Moreover, it can be seen from the correlation matrix that the dataset is not affected by the issue of multi-collinearity (correlation coefficient of almost all the variables are below 0.6).

To obtain information of people's perception of HH energy sector, we asked a question as a proxy to all the respondents: "Do you think that the existing energy availability and technologies you are using in your household are sufficient to meet your current and future energy needs?" Three possible responses were *Agree, Disagree* or remain *Neutral*. People agreeing to our question did not feel the need to adopt any changes to their HH energy. However, people disagreeing to our question identified the need to make changes in the energy sources as well as consumption pattern for a better and sustainable energy secure future. The respondents who remained neutral were mostly either unaware of the possible energy alternatives or were constrained financially and socially. It can be seen that the spread of the response (perception) variable in our dataset is relatively balanced across the three labels of *Agree* (34%), *Neutral* (24%) and *Disagree* (41%) (Fig. 3).

5.2. *Evaluation of models*

Seven machine learning models were fitted to the HH data collected during field survey and six performance metrics were evaluated for each model (Table 3). The models were evaluated against each label of the 'Perception' variable (*Agree, Neutral* and *Disagree*) (Annex Table B1). Additionally, each response of the 'Perception' class was further segregated when the response conditions was met (shown by *TRUE*) or otherwise (*FALSE*), as listed in the fourth column of Table 3. It is essential to analyze these metrics within the specific problem and domain context. For example, precision is a more suitable metric when "False Positives" are of a higher concern than "False Negatives". Similarly, recall is usually a better option when "False Negatives" are more important than "False Positives" [114,115]. Hence, *confusion matrix, precision, recall* and *f1 score* was calculated for each combination and the overall accuracy of the model to predict each response class was then evaluated. It can be seen that *Multi-Layer Perceptron (MLP), Multinomial Regression – Logit (MR-L)* and *Multinomial Regression – Probit (MR-P)* have the poorest performance in estimating the response of the predictand variable in all the combinations of the metrics tested. For example, the *MLP* estimates *Agree* with a *precision* of 0.53, *recall* of 0.42 and *f1 score* of

Table 1
Seven machine learning models adopted in this study.

S. N.	Model	Type	Features
1	K-Nearest Neighbors (KNN)	Non-parametric and instance-based	Assumes that similar instances or data points tend to exist in proximity in the feature space
2	Multi-Layer Perceptron (MLP)	Neural networks	Functions by defining the input and output layers, assigning weights to the connections between neurons, and applying activation functions
3	Extra Trees Classifier (ETC)	Tree-based	Is an ensemble learning method where multiple decision trees are trained on different subsets of the training data and their predictions are combined to make final predictions
4	Random Forest (RF)	Tree-based	Combines multiple decision trees to solve classification tasks trained on a randomly sampled subset of the training data, and the final prediction is determined by aggregating the predictions of all individual trees
5	Ridge Classifier (RC)	Linear	Is a linear classifier for multilabel classification tasks based on Ridge Regression (regularized with L2-norm penalty)
6	Multinomial Regression – Logit (MR-L)	Regression-based statistical	Is a type of regression analysis used to model the probability of a binary outcome assuming the relationship between the dependent variable and the independent variables is linear on the logit scale
7	Multinomial Regression – Probit (MR-P)	Regression-based statistical	Is a type of regression analysis used to model the probability of a binary outcome assuming linear relationship between the dependent variable and the independent variables which is transformed using the cumulative distribution function

Information sourced from Das et al. [29]; Diesenroth et al. [61]; Er et al. [109]; Kumaravelan and Behera [110]; Storm et al. [60]; Wu et al. [111]; and Zhang and Zhou [112].

0.47 in the case of 80:20 training-testing split. The confusion matrix of the *True-Agree* class shows that 30 positives were predicted correctly (true positives – shown in the first row and first column of the confusion matrix) while 17 true negatives were predicted correctly (second row, second column of the confusion matrix). The errors are 15 false positives and 23 false negatives. Similarly, the model is able to estimate *False-Agree* with a *precision, recall* and *f1 score* of 0.57, 0.67 and 0.61 respectively. The *balanced accuracy* of the model for the *Agree* condition is 0.55. The *Extra Trees Classifier (ETC)* model demonstrated a *balanced accuracy* of 0.79, 0.95 and 0.68 for the *Agree, Neutral* and *Disagree* categories. We performed cross-validation of the models for three more scenarios based on the training-testing data split taking 70:30, 60:40 and 50:50 values. Carrying out a number of cross-validation simulations is a standard practise in ML to evaluate the robustness of all the models. From these scenarios, it is evident that *ETC* outperformed the other models in terms of all six evaluation metrics. Hence, *ETC* has been selected as the best fit model in explaining all three classes of the response variable of our dataset.

5.3. Feature importance

The relative feature importance of the considered 14 variables in explaining the three labels (*Agree, Neutral* and *Disagree*) of the response variable derived from the best fit *Extra Trees Classifier (ETC)* model has been presented in Fig. 4. The values for each label (column) add up to one. The relative importance of the variables ranges from 2.5% (*Agree*: 'Ethnicity') to 13.1% (*Agree*: 'Occupation') across all the three output categories. For the *Agree* category, 'Occupation' has the highest contribution of 13.1%, followed by 'Major energy source' contributing 10.5%. Similarly, the third in row is 'Second energy source' (9.6% contribution), 'Development status' ranks fourth (8.4%) followed by 'Literacy' (8.1%). These five factors are capable of explaining a cumulative 50% response in the *Agree* category. 'Ethnicity' has the least contribution of 2.6%. Similarly, 'Self-assessment' (12% contribution), 'Physiography' (10.7%), 'Income' (9.1%), 'Family size' (8.4%) and 'Development status' and 'Age' (8% each) respectively rank first to fifth in the *Neutral* category. Likewise, 'Occupation' (11.2%), 'Development status' (10.6%), 'Income' and 'Family size' (9.1% each), 'Literacy' and 'Second major energy' (8% each), and 'Ethnicity' (7.2%) are respectively the top five contributors of the *Disagree* response category. 'Gender' was found to have the least contribution in both the *Neutral* (3.3%) and *Disagree* (4.1%) response categories.

It is seen from Fig. 4 that 'Development status' is common among the top five influencing variables for all the three labels of the response variable. 'Occupation' and 'Literacy' are common between the *Agree* and *Disagree* labels. Similarly, 'Income' and 'Family size' are common across the *Neutral* and *Disagree* categories. Additionally, 'Load centre' and 'Age' are among the variables that have moderate effect (sixth to tenth in line) on all the three labels of the response variable. Interestingly, 'Gender' is among the least influential variables for all the three labels. 'Ethnicity' is common in the last four ranking variables between the *Agree* and *Neutral* categories. Moreover, 'Physiography' is common in the last four explanatory variables among *Agree* and *Disagree* while 'Vehicle ownership' is between *Neutral* and *Disagree* categories.

5.4. People's perception

Cross tabulation of the explanatory variables with the response variable, considering the sample of 323 datasets, allowed for visualization of the distribution across their different categories (Table 4). For instance, across the 'Primary occupation' category, a considerable number of people working in the private organizations (31) felt that the current energy supply and consumption at their HHs is adequate for meeting the current and future energy needs while a sizeable number of self-employed people (42) felt the need of change at their HHs; the largest group remaining *Neutral* are farmers (33), results being significant at 95% confidence level. Similarly, a sizable number of HHs earning more than USD 1,960 per year felt the need for a change in the energy behaviour (73) while a fair number of HHs (52) felt otherwise ($p < 0.05$). Likewise, in the 'Physiography' category, most of the people living in the mid hills either want a change in the HH energy behaviour (52) or do not prefer any changes (74) while a majority with *Neutral* (32) responses were from the high hills (results significant with $p < 0.05$). Additionally, it can be seen that most respondents from the rural (45) and semi-urban (46) areas perceived that the current conditions of HH energy is adequate. On the other hand, a considerable number of people from semi-urban (63) areas felt that there is a need for change in the existing energy status of their houses. Thus, it is evident that the responses pertaining to the people's perception and response vary across the different categories of the explanatory variables (Table 4).

6. Discussion

6.1. Application of machine learning

An important reading from Fig. 4 is that none of the explanatory variables have a contribution larger than 13% in explaining the output response across all labels. This is a validation that the variables used for this study are all important but with varying relative influences. It is to be noted that feature importance values (Fig. 4) are different from

Table 2
Performance metrics used to evaluate the machine learning methods in our study.

S.N.	Metric	Explanation	Mathematical denotation
1	Confusion matrix	Is a table used to evaluate the performance of a classification algorithm on a set of test data for which the true values are known. It summarizes the number of correct and incorrect predictions made by the algorithm, broken down by each class in the problem.	Actual Labels: Positive / Negative. Predicted Labels Positive: True Positives (TP), False Positives (FP). Predicted Labels Negative: False Negatives (FN), True Negatives (TN)
2	Accuracy	Accuracy is the proportion of correctly classified data points (sum of the diagonal elements of the confusion matrix divided by the total number of sample points).	$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$
3	Balanced Accuracy	In multi-label classification, the concept of balanced accuracy can be extended to compute the accuracy as defined earlier for each individual label and then take the average of these accuracies.	Same as for 'Accuracy' but calculated for each label separately
4	Precision	Precision is the proportion of correctly classified positive predictions (i.e., true positives divided by the sum of true positives and false positives).	$Precision = \frac{TP}{TP + FP}$
5	Recall	Recall (also called sensitivity) is the proportion of actual positive instances that are correctly classified (i.e., true positives divided by the sum of true positives and false negatives)	$R = \frac{TP}{TP + FN}$
6	F1 score	F1 score is the harmonic mean of precision and recall, which provides a single measure of overall performance.	$F1\ score = 2\ \frac{(Precision * Recall)}{(Precision + Recall)}$

Information sourced from de Carvalho and Freitas [113]; Heydarian et al. [114]; Tsoumakas and Katakis [115]; Vaizman et al. [116]; Wu et al. [111]; Zhang et al. [117]; and Zohair [118].

regression coefficients (that are obtained from regression analysis and used to analyze the marginal effect of a particular variable on the regressed variable). This study is about classification and not prediction/regression. Hence, the commonly used evaluation indicators such as mean absolute error (MAE), mean relative error (MRE), root mean square error (RMSE), correlation coefficient (R), coefficient of variation (R^2 or its variants such as pseudo-R^2, adjusted R^2, etc.) have not been used in our analysis because these are generally applicable to linear regression unlike data driven models [61,66]. Instead, we have chosen to adopt a more robust set of evaluation metrics comprising of *confusion matrix, precision, f1 score, recall* and *accuracy* for checking the applicability of the models to the considered dataset. The confusion matrix is able to clearly provide evidence of the true and false estimations of a particular response class.

In this study, we adopted seven ML models: *RF* and *ETC* (tree-based), *MR-L* and *MR-P* (statistical), *KNN* (non-parametric and instance-based), *RC* (linear) and *MLP* (neural networks). Based on the evaluation results (Table 3), tree-based models outperformed other models in multi-label classification of people's perception of HH energy. Among the tree-based models, *ETC* achieved the best performance in terms of all six evaluation metrics. The popularly used statistical models *MR-L* and *MR-P* were the least performing. This proves the need for exploring models other than linear/conventional statistical models to better analyse such non-linear social behaviour.

In ML applications, there is a general issue of class-imbalance meaning that the trained model is likely to be biased towards the majority class [119,117]. We adopted random oversampling technique to balance multi labels as a standard practise [120–122]. Furthermore, to evaluate the performance of each ML model in classification of each label, we implemented the *balanced accuracy* metric (in addition to *overall accuracy*) which calculates the accuracy of classifying each label [118]. We found that *ETC* model performed the best in all the scenarios irrespective of the test-train data split.

Furthermore, an advantage of using tree-based ML models is that the process of assigning features importance to the explanatory variables with respect to the response variable can be conveniently explained using tree visualization [123]. The tree visualization is constructed by recursively splitting the training data into smaller subsets based on the feature combination that provides the most information gain. To build a tree, the algorithm evaluates the different features to determine which

Table 3
Evaluation of models in explaining the *Agree, Neutral* and *Disagree* classes of the 'Perception' variable.

S.N	Models	Perception Class	Boolean condition	Confusion Matrix	Precision	Recall	F1 score	Balanced Accuracy	Overall Accuracy
1	K-Nearest Neighbors (KNN)	Agree	FALSE	[[23 17] [21 24]]	0.59	0.53	0.56	0.55	0.54
			TRUE	[[24 21] [17 23]]	0.52	0.57	0.55		
		Neutral	FALSE	[[33 20] [19 26]]	0.57	0.58	0.57	0.60	
			TRUE	[[26 19] [20 33]]	0.63	0.62	0.63		
		Disagree	FALSE	[[17 18] [17 24]]	0.57	0.59	0.58	0.54	
			TRUE	[[24 17] [18 17]]	0.50	0.49	0.49		
2	Multi-Layer Perceptron (MLP)	Agree	FALSE	[[17 23] [15 30]]	0.57	0.67	0.61	0.55	0.51
			TRUE	[[30 15] [23 17]]	0.53	0.42	0.47		
		Neutral	FALSE	[[25 28] [20 25]]	0.47	0.56	0.51	0.51	
			TRUE	[[25 20] [28 25]]	0.56	0.47	0.51		
		Disagree	FALSE	[[8 27] [13 28]]	0.51	0.68	0.58	0.47	
			TRUE	[[28 13] [27 8]]	0.38	0.23	0.29		
3	Extra Trees Classifier (ETC)	Agree	FALSE	[[33 7] [7 38]]	0.84	0.84	0.84	0.84	0.74
			TRUE	[[38 7] [7 33]]	0.82	0.82	0.82		
		Neutral	FALSE	[[52 1] [5 40]]	0.98	0.89	0.93	0.94	
			TRUE	[[40 5] [1 52]]	0.91	0.98	0.95		
		Disagree	FALSE	[[19 16] [4 37]]	0.70	0.90	0.79	0.74	
			TRUE	[[37 4] [16 19]]	0.83	0.54	0.66		
4	Random Forest (RF)	Agree	FALSE	[[30 10] [15 30]]	0.75	0.67	0.71	0.71	0.68
			TRUE	[[30 15] [10 30]]	0.67	0.75	0.71		

(*continued on next page*)

Table 3 (*continued*)

		Neutral	FALSE	[[49 4] [10 35]]	0.90	0.78	0.83	0.86	
			TRUE	[[35 10] [4 49]]	0.83	0.92	0.88		
		Disagree	FALSE	[[21 14] [10 31]]	0.69	0.76	0.72	0.68	
			TRUE	[[31 10] [14 21]]	0.68	0.60	0.64		
5	Ridge Classifier (RC)	Agree	FALSE	[[21 19] [18 27]]	0.59	0.60	0.59	0.56	0.53
			TRUE	[[27 18] [19 21]]	0.54	0.53	0.53		
		Neutral	FALSE	[[26 27] [16 29]]	0.52	0.64	0.57	0.56	
			TRUE	[[29 16] [27 26]]	0.62	0.49	0.55		
		Disagree	FALSE	[[14 21] [15 26]]	0.55	0.63	0.59	0.53	
			TRUE	[[26 15] [21 14]]	0.48	0.40	0.44		
6	Multinomial Regression – Logit (MR-L)	Agree	FALSE	[[21 19] [25 20]]	0.51	0.44	0.48	0.48	0.51
			TRUE	[[20 25] [19 21]]	0.46	0.53	0.49		
		Neutral	FALSE	[[50 3] [41 4]]	0.57	0.09	0.15	0.55	
			TRUE	[[4 41] [3 50]]	0.55	0.94	0.69		
		Disagree	FALSE	[[3 32] [5 36]]	0.53	0.88	0.66	0.51	
			TRUE	[[36 5] [32 3]]	0.38	0.09	0.14		
7	Multinomial Regression – Probit (MR-P)	Agree	FALSE	[[21 19] [25 20]]	0.51	0.44	0.48	0.48	0.51
			TRUE	[[20 25] [19 21]]	0.46	0.53	0.49		
		Neutral	FALSE	[[50 3] [41 4]]	0.57	0.09	0.15	0.55	
			TRUE	[[4 41] [3 50]]	0.55	0.94	0.69		
		Disagree	FALSE	[[3 32] [5 36]]	0.53	0.88	0.66	0.51	
			TRUE	[[36 5] [32 3]]	0.38	0.09	0.14		

Note: This table presents the evaluation metrics of the models training and testing carried out at 80:20 split of the data. Randomized oversampling has been introduced to remove the data-related bias for model training and testing (n=323).

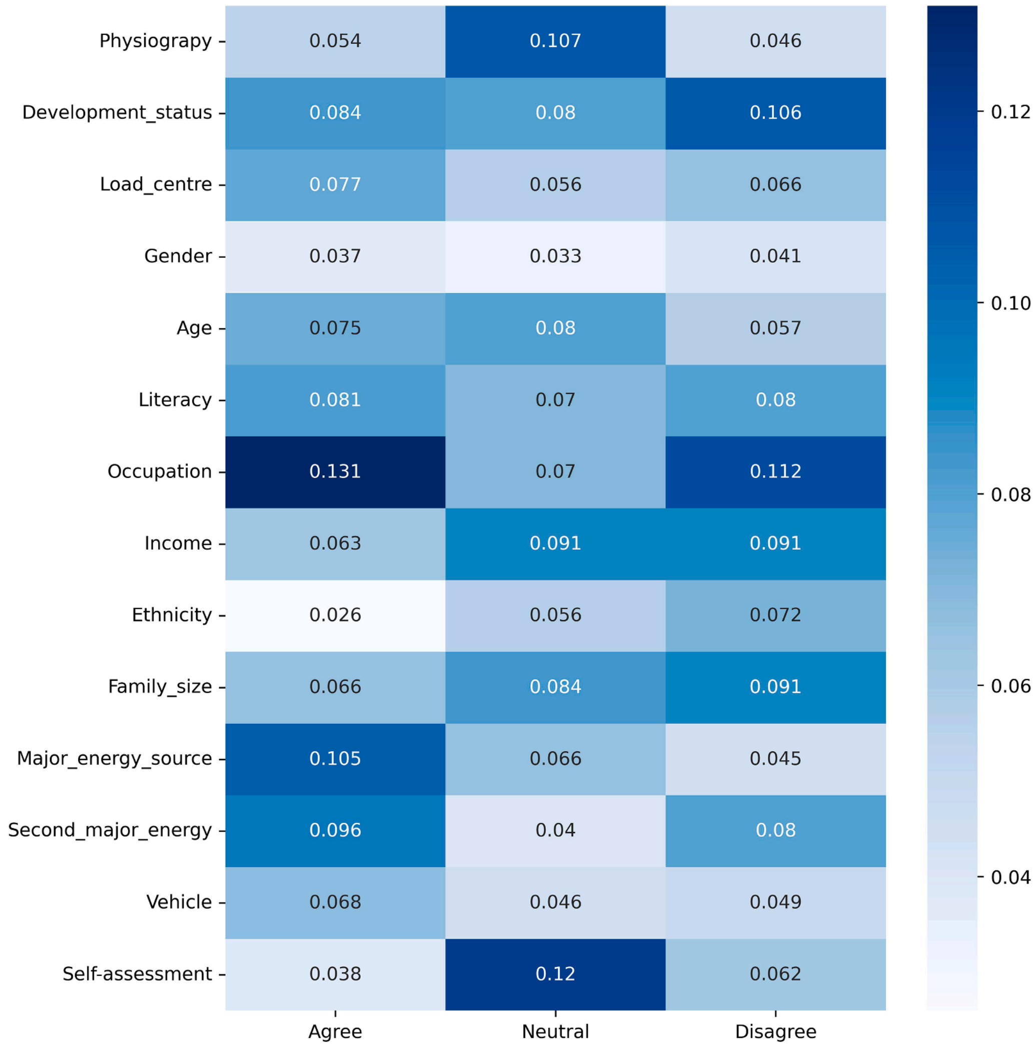

Fig. 4. Heat map of feature importance of the explanatory variables against the three classes, *Agree, Neutral* and *Disagree*, of the response variable derived from the *Extra Trees Classifier (ETC)* model.

one provides the most information gain, i.e., the feature that maximizes the separation of the classes or reduces the variance of the response variable [111] as shown in Fig. 5. The tree we have presented here for the purpose of illustration is one among the many considered in the analysis. In this figure, the 'second major energy source' (depth=1) has the highest information which is further split into two categories: first with class 1 ('grid-electricity'), 2 ('LPG'), and 3 ('petroleum') which is shown on the left-hand side and the second with class 4 ('renewables') shown on the right-hand side. The second level split (depth = 2) is based on 'gender' while the third level split (depth = 3) is based on 'ethnicity', 'load centre' and 'occupation', depending upon their classes. The process is further continued until the information of the entire dataset is converged. Also, each class of all the explanatory variables is segregated according to three labels of the response variable (denoted by yellow: *Agree*, blue: *Neutral*, and green: *Disagree*) for each depth (Fig. 5). The final values of feature importance obtained from the *ETC* model is calculated by taking an average of multiple trees formed in the same way. For example, if a tree-based model is trained using 100 trees, the final feature importance of the explanatory variables and classification of multi-labels of response variable are derived based on the average of the 100 trees.

6.2. Public perception of HH energy

Energy consumption patterns in Nepalese households are such that cooking is the primary use of energy, while lighting and other uses have lower consumption values [99,124]. Room heating/cooling is not that common. Traditional heating mechanism include bonfires in open areas or charcoal fire in iron pans for room heating. The Terai (southern plains) has a relatively hotter climate and those HHs that can afford, use table or ceiling fans mostly during summer. The hilly areas are cooler and people who can afford buy electric or LPG heaters. Air-conditioners/coolers and central heating/cooling systems are limited to the upper most class of the urban areas.

It was found that residents of the rural and semi-urban areas tend to resist changing energy sources due to economic constraints and lack of awareness (example response Annex D1). On the contrary, most people living in the urban areas were found more open to change due to better economic conditions and education. This is evident from the fact that 'Occupation' and 'Literacy' are the most influencing features common across the *Agree* and *Disagree* categories (Fig. 4). People's willingness to pay for electricity generation from renewables as a better option for the future has been reported by studies such as Chaikumbung [58]. Moreover, people in the urban areas generally have a smaller family size and better incomes which can afford expensive modern fuels [125,126]. As a

Table 4
Cross tabulation results of the explanatory variables and people's perception (count) on the continuation of current energy sources for energy security at the household level.

Explanatory variables	Classes	Perception			Total	Chi-square (p-value)
		Agree	Neutral	Disagree		
Physiography	High hills	34	32	29	95	**9.727 (0.045)**
	Mid hills	52	29	74	155	
	Terai (plains)	25	18	30	73	
Development status	Rural	45	29	34	108	7.281 (0.121)
	Semi-urban	46	32	63	141	
	Urban	20	18	36	74	
Family size	Nuclear (<=4)	49	38	57	144	1.831 (0.766)
(Mean: 4.9; SD: 1.9)	Extended (4-6)	42	32	55	129	
	Joint (>6)	20	9	21	50	
Gender	Female	16	25	27	68	**8.321 (0.015)**
	Male	95	54	106	255	
Age	20-35	48	28	61	137	2.374 (0.667)
(Mean: 40.6; SD: 13.6)	35-50	34	28	41	103	
	>50	29	23	31	83	
Literacy	Illiterate	15	20	8	43	4.592 (0.331)
	Primary school/ Informal education	12	13	21	46	
	Secondary/ High school	38	27	50	115	
	University	46	19	54	119	
Load centres	Kathmandu	27	22	38	87	5.817 (0.213)
	Other towns	18	12	33	63	
	Others	66	45	62	173	
Self evaluation	Agree	73	33	99	205	**41.733 (0.000)**
	Disagree	20	7	15	42	
	Neutral	18	39	19	76	
Second major energy source	Grid-electricity	62	43	80	185	4.886 (0.558)
	LPG	37	21	39	97	
	Petroleum	8	8	8	24	
	Renewables	4	7	6	17	
Annual household income (USD)	< 692	20	28	20	68	**19.015 (0.004)**
	692 – 1,154	13	12	12	37	
	1,154 – 1,960	17	14	22	53	
	> 1,960	52	23	73	148	
	ND	9	2	6	17	
Major energy source	Agriculture-residue	19	10	10	39	11.455 (0.177)
	Grid-electricity	30	17	26	73	
	LPG	55	43	83	181	
	Petroleum	5	7	13	25	
	Renewables	2	2	1	5	
Primary occupation	Academic/ government service	16	5	23	44	**22.385 (0.004)**
	Farming/ livestock rearing	26	33	24	83	
	Private organization	31	13	34	78	
	Self-employed	25	18	42	85	
	Unemployed/ retired	13	10	10	33	
Total		111	79	133	323	

Bold *p*-values are significant at 95% confidence level; ND: preferred not to disclose

result, 'Income' and 'Family size' are found to be among the common influencing features in the *Neutral* and *Disagree* categories.

Contrary to our expectation, the sources of energy that people are currently using ('Major energy source' and 'Second major energy source') have varying influences on the response classes (Fig. 4 and Table 4). Grid electricity was found to be the major energy source in areas which are connected to the national grid. LPG was found to be the major energy source for HHs in most urban and semi-urban areas for cooking. People having access to grid electricity and LPG (mostly in the urban areas with a better economic condition) do not choose to make any changes to their HH energy condition for future energy sufficiency (example responses in Annex D2 and Annex D3). On the other hand, the existing sources of energy were not found to be that important for the *Neutral* and *Disagree* response classes, irrespective of their location or economic condition.

'Age' and 'Gender' were seen to respectively have moderate and the least influence on all the three response categories (Fig. 4). We consider this reasonable as female members mostly have little say on the choice of HH energy technologies, an observation common across the rural, semi-urban and urban areas of Nepal [29,59]. The response of the male members of the family varied by location, occupation, income level, awareness and age. Furthermore, extended and joint families are common in Nepal, and it is not always the HH head that decides on the use of energy technologies. The younger members of the family are generally more educated and are better exposed to latest technologies. Moreover, the young and educated are likely to earn more and have a better influence in energy related decisions at the HH level.

6.3. Rural HH energy

Rural cooking of Nepal relies on traditional fuels (firewood, dry dung and agriculture residue) while LPG and kerosene are the mostly used urban cooking fuels. In rural areas, 51% of the population depends on firewood for cooking, 2.9% use dried dung while only 1.2% use bio-gas and less than 1% use kerosene or other sources [124]. The marginalized and the most disadvantaged are still the largest sufferers in terms of inclusiveness in energy access and use. A HH being connected to the national electricity grid is still considered a status symbol in Nepal, particularly in the remote areas (example: electric cooktop in Fig. 1). Therefore, reliance on traditional fuels is extremely high (examples shown in Fig. 1). Moreover, there is ethnicity/caste-based differentiation in cooking energy [76,127]. Firewood is directly collected from

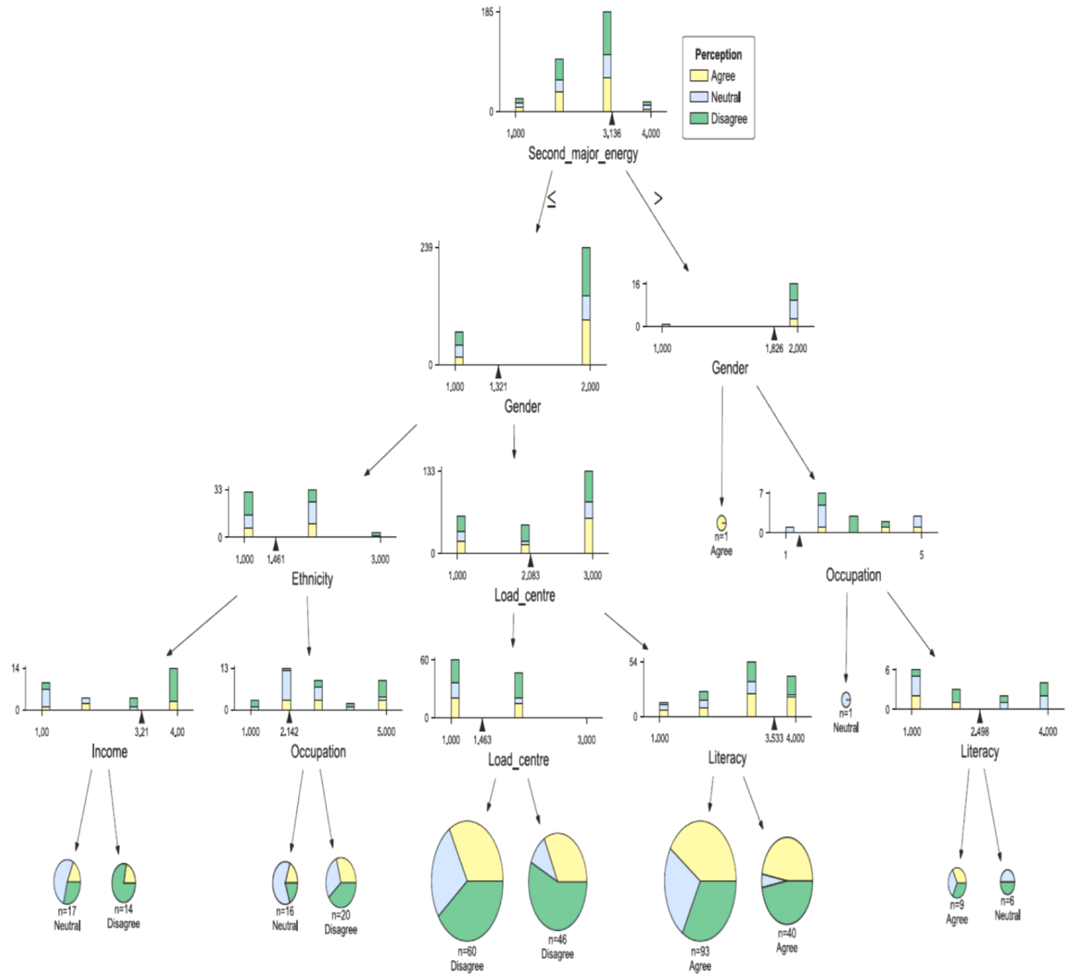

Fig. 5. Process of assigning features importance to the explanatory variables with respect to the response variable using tree-based visualization. A sample tree is presented here for illustration.

privately sources or nearby (community managed or national) forests at cheap rates [128]. Dried dung (called 'guitha' in local dialect) is prepared mixing cows/buffalo dung with husk, hay and firewood. They are sundried and commonly used as fuel for cooking (example response in Annex D1). 'Guitha' is prepared in a circular shape in the hills while they are mostly wrapped around firewood in the Terai plains of Nepal (Fig. 1). Generally, making 'guitha' is considered a household chore and women are responsible for it [129]. Interestingly, our survey team observed a recent trend of switching to LPG[1] from traditional (wood and 'guitha') stoves in the rural areas in all the three physiographic regions (example picture of mule carrying LPG cylinder on its back in a remote village in Gorkha in Fig. 1).

Fuelwood and 'guitha' are managed by the people irrespective of whether they get any external support because it is for one of the basic needs of life — food [38]. That could be the main reason why the government has not been eager to initiate programs to replace traditional fuels with modern renewables. Furthermore, there is evidence of developing countries having to spend one-fifth of their income on wood for cooking, devoting one-quarter of domestic labour collecting fuelwood and ultimately suffering from life-ending pollution from inefficient combustion [130].

Off-grid small scale renewable energy technologies such as microhydro, solar PV, biogas and hybrid systems are relatively cheaper options for the rural areas (Fig. 1) because of their low capital cost and large government subsidies [33,107]. AEPC [131] reports that the total national installed capacity of rooftop solar PV is 10 MW, that of micro and mini-hydropower is 37.7 MW and local hybrid grids is 3 MW. Formulation of the Renewable Energy Subsidy Policy 2006, 2009, 2013, 2016 and 2022, establishment of AEPC in 1996, provisioning of Renewable Energy Fund (REF) in 2002 and the Central Renewable Energy Fund (CREF) in 2007 can be considered as milestones in this regard [132]. Similarly, considerable increase in the number of biogas plants and international support, for example through SNV from 1992, GTZ between 1997 and 2011 [133,134], are notable achievements. In many cases, even the subsidized monthly electricity fare becomes too high for a large majority of the rural community to afford [135]. Moreover, small off-grid energy systems are not sustainable in the long run as modern electronic appliances require more energy than that provided by small panels and LEDs as people move up the energy ladder [28]. Additionally, one-time subsidy particularly for rural communities have been proven ineffective in many instances (example response in Annex D1). A similar resistance was found in cooking in Chile which warranted efficient management of impacts due to multiple social factors [136]. Most of our rural respondents were found unaware about how they can switch to better energy alternatives through government subsidies; and how they are economically and environmentally beneficial in the long run. This leads to reluctance in transitioning to modern fuels and technologies.

Complementary technologies such as wind-solar PV-hydropower have been tested in Latin America with promising results [137]. With the recent construction of large hydropower projects, grid extension to

[1] It is noted here that 1 kg of LPG has a useful energy value of 20.7 MJ which is equivalent to 21.2 kg of raw wood burnt in conventional stoves [129].

rural hilly and mountainous areas has gained momentum after the mid-1990s [33]. However, not all such projects have been welcomed by the people (example response in Annex D4). Moreover, micro-hydro based mini-grid technologies have been recommended for developing countries such as Nepal [40,138–140]. Technology transfer and donations without proper ecosystem development have also proven inefficient [33]. Hence, the choice of off-grid technologies needs to be rationally made based on their fit to the local context.

6.4. HH energy use in urban areas

Kathmandu Valley is the largest load centre followed by other smaller cities. Despite boasting a 93% electrification rate of Nepal in 2022 by GoN [100], reliability and usability of the supplied electricity are poor because of which the per capita electricity consumption is low (229 kWh/year) [141]. Nepal has struggled to tap into its significant renewable energy potential [34,142,143]. As a result, loadshedding (a scheduled power outage) was implemented in 1992, lifted in 2000, reintroduced in 2006, and finally ended in 2018 due to improved management and power imports from India [100]. As Movik and Allouche [144] mention, Nepal has had to go through a ‘chaotic fragmentation of the energy landscape’. Moreover, political instability, social acceptance issues, and lack of energy transition management capabilities have contributed to sluggish power sector development in South Asia [145], including Nepal.

Studies have found that even in urban areas where people have the financial capacity, they are hesitant to climb up the ‘energy ladder’ [59,70] due to a lack of trust and reliability (example responses in Annex D2 and Annex D3). Fuel-stacking is prevalent, where people rely on multiple fuel options due to uncertainty about existing supplies [59]. While people express a willingness to pay more for reliable electricity supply at the HH level [29], past incidents of the 1988 and 2016 economic blockades on Nepal by India and the 2015 Great Earthquake have undermined public trust in the state’s fuel supply. As a result, urban HHs continue to use various fuel options, including grid electricity, LPG, kerosene, rooftop solar PV, and firewood, instead of transitioning fully to renewable energy (example responses in Annex D). Semi-urban areas demonstrate energy patterns which are in between the rural and urban contexts.

With the enactment of Hydropower Policy 1992, 2001 and Water Resources Act 1992, 2002, the country has made efforts of developing micro-, small- and large-hydropower projects, targeting the urban and rural areas alike. As a result, the cumulative hydropower installed capacity of the nation stands at 2205 MW in 2022 [100]. However, there is a lack of concrete measures to replace traditional fuel consumption at the household level. The ambitious targets set in policies like the Water Resources Strategy (generating 22,000 MW hydropower by 2027), the National Water Plan (generating 4,000 MW hydropower by 2027 with increased per capita electricity consumption), and the Second Nationally Determined Contribution 2020 (ensuring achieving 25% electric stoves by 2025) is not likely to be met under current conditions.

Increasing electricity tariffs has been recommended as one of the options for increasing the efficiency of Nepal’s electricity sector [146]. However, this does not seem feasible because a large share of the current Nepalese population (even in the urban areas) is already unable to afford electricity at the existing price (example responses in Annex D1, Annex D2 and Annex D3). Similar findings have been reported in Chile in which electrification of firewood for space heating can lead to energy poverty conditions for the people in the lowest socio-economic category [147].

Furthermore, studies have shown that research on the development and use of multiple types of energy sources and national level planning are slowly gaining attention in Nepal [72,127,148,149]. Chen [150] concludes that national efforts of controlling energy consumption by ‘regulation priority’ and ‘technology-driven and industrial structure upgrading’ have played a key role in China’s decarbonization. In the context of Nepal, strengthening local cooperatives and financial institutions and motivating them to invest in and promote energy-efficient devices is important [33,151]. Although diversification of the energy generation mix has been the current focus of Nepal’s energy policies, it has not been seen to be effective [152]. Furthermore, Nepal lacks the domestic capacity to adapt to changing energy conditions, particularly in the context of climate change [153]. Our results indicate that a bottom-up trajectory is required for policy formulations with active involvement of the stakeholders [32,154] because policies are usually guided by public demands (example responses in Annex D4, Annex D5 and Annex D6). Incorporating these grass-root level issues during policy formulation and implementation paves way for sustainable development.

7. Conclusion

Social and behavioural sciences in energy research have been outcasted by the ‘hard’ disciplines such as economics, statistics, physics, mathematics and engineering. Hence, catering to the social aspects of energy research in a developing country is a key contribution of this study. In this multidisciplinary research, we explained the social behaviour of the general public with regards to household energy taking the case of a South Asian country – Nepal using machine learning models. We adopted a mixed-method approach consisting of six stages: household survey, data pre-processing, application of seven ML models, evaluation of the models based on six performance metrics, selection of the best model and explaining people’s perception. We carried out cross-sectional survey gathering data from 323 households to extract 14 independent (predictor) variables and one response variable with three labels.

Our results showed that, compared to conventional statistical models, data driven ML models are better in classifying non-linear social responses. Furthermore, among the ML models, tree-based models were found to be more robust and have better interpretability of the process to arrive at the feature importance. In our particular dataset, the *Extra Trees Classifier (ETC)* was the best fitting model which demonstrated a *balanced accuracy* of 0.79, 0.95 and 0.68 respectively for the *Agree, Neutral* and *Disagree* categories of the response variable.

We found that ‘Development status’ has a large role in people’s perceptions. It was seen that people from rural and semi-urban areas tend to resist changing their current energy sources and consumption pattern due to economic constraints and lack of awareness. Fuelwood and ‘guitha’ are managed by the rural people irrespective of whether they get any external support because it is for one of the basic needs of life — food. However, a recent trend of switching to LPG from traditional fuels was observed in the rural areas in all the three physiographic regions which is extremely counter-productive. Off-grid small scale renewable energy technologies such as micro-hydro, solar PV, biogas and hybrid systems are relatively cheaper options for the rural areas because of their low capital cost and large government subsidies. Moreover, such small off-grid energy systems are not sustainable in the long run as modern electronic appliances require more energy than that provided by these technologies as people move up the energy ladder. The marginalized and the most disadvantaged are still the largest sufferers in terms of inclusiveness in energy access and use. Urban residents with access to electricity grid and LPG were found against switching to better alternatives; rather fuel-stacking is prevalent due to a lack of trust and reliability in the government. Furthermore, there is a lack of concrete measures from the government to replace traditional fuel consumption at the household level despite some progress at the policy level. As a result, the ambitious targets set out in the policies are not likely to be met under current conditions.

Hence, lack of awareness, financial constraints and trust in modern and efficient energy technologies are evident from the grass-root level responses compiled in this research. Comprehending people’s voices from bottom-up is necessary for effective policy making, planning and implementation, particularly in the developing world. Moreover, it is important to consider country-specific factors and involve stakeholders in the planning and implementation processes for an altered energy landscape of Nepal. Small off-grid technologies could be a temporary rural measure, but Nepal should aggressively promote domestic hydropower and other renewables to cater to the household energy demands of both urban and rural areas.

There were limitations in our study, particularly related to the sample size, type of survey, and number of ML models used. Additionally, understanding people's perception can be extended to their preference of transitioning to better alternative energies at the HH level of Nepal. Moreover, a longitudinal survey at a regular interval could be another arena for extension of this research to analyse the temporal pattern of change in people's perception. Similarly, the choice of an appropriate ML model is highly dependent on the type of data it can process. Our primary criterion for selecting the seven models is their ability to handle categorical and multi-label data. There might be other complex ML models that fit this criterion. However, the models evaluated in this study were chosen because of their simplicity in execution and interpretability. Incorporating other models in the evaluation framework could be explored further.

CRediT authorship contribution statement

Utsav Bhattarai: Conceptualization, Methodology, Data curation, Software, Formal analysis, Writing – original draft. **Tek Maraseni:** Conceptualization, Supervision, Writing – review & editing. **Laxmi Prasad Devkota:** Supervision, Writing – review & editing. **Armando Apan:** Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Annex A

Table A1

Table A1
Survey districts selection criteria.

S. N	Survey districts	Sample size	Physio-graphy	Dev. Status	Electri-fication status	Alt. electricity	Remarks
1	Kathmandu/ Bhaktapur / Lalitpur	60	Mid hills	Urban/ semi-urban	Electrified	HH solar	Core city/ semi-urban areas
2	Makwanpur/ Chitwan / Nawalpur	30	Mid hills / Terai	Semi-urban	Electrified/ non-electrified	HH/ local grid solar/ micro hydro/ diesel	Kulekhani cascade, Lower Bagmati hydropower and diesel plant areas
3	Gorkha/ Lamjung/ Tanahu/ Kaski/ Baglung	45	High hills/ Mid hills	Semi-urban/ rural	Electrified/ non-electrified	HH/ local grid solar/ micro hydro	Budhigandaki, Marsyangdi and Tanahu hydropower project areas
4	Rautahat/ Bara / Dhanusha / Siraha/ Mahottari	45	Terai	Semi-urban/ rural	Electrified/ non-electrified	HH/ local grid solar/ micro hydro	Bagmati multipurpose project & Chandranighapur Solar project areas
5	Dolakha/ Ramechhap/ Kabhrepalanchok/ Sindhupalchok	45	Mid hills/ High hills	Urban/ semi-urban/ rural	Electrified/ non-electrified	HH/ local grid solar /micro hydro	Upper Tamakoshi, Khimti hydropower & Sunkoshi cascade project areas
6	Sankhuwasabha/ Illam/ Jhapa	30	High hills/ Mid hills/ Terai	Semi-urban/ rural	Electrified/ non-electrified	HH/ local grid solar/ micro hydro	Arun III/ Kimathanka and many other hydropower project areas
7	Morang/ Sunsari	30	Terai	Urban/ semi-urban	Electrified	HH/ local grid solar/ diesel	Duhabi industrial corridor/ Biratnagar/ Dharan
8	Dolpa/ Rukum West/ Dailekh / Surkhet / Achham/ Bajhang / Baitadi / Darchula	35	High hills	Rural	Electrified/ non-electrified	HH/ local grid solar/ micro hydro	
9	Banke/ Bardiya/ Kailali/ Kanchanpur	30	Terai	Urban/ semi-urban/ rural	Electrified/ non-electrified	HH/ local grid solar/ micro hydro	Biggest solar project, Bhalubang, Naumure & other project areas
	Total	**350**					

Annex B

Table B1

Table B1
Adopted explanatory and response variables with their classes and justification for the classification.

S. N	Variables	Given name	Classes	Code	Justification
Explanatory variables					
1	Physiographic region	*Physiography*	High hills Mid hills Terai (plains)	1 2 3	Nepal can be broadly categorized into four physiographic regions, among which we excluded the High Mountains. There are distinct prominent energy generation and consumption practices in the respective physiographic regions. Hence, this categorization has been adopted to capture such variation.
2	Development status	*Development_status*	Rural Semi-urban Urban	1 2 3	The energy sources available to the rural, semi-urban and urban areas differ very much. As a result, the consumption practices are also remarkably different. Therefore, this heterogeneity has been captured in our survey through the adopted categorization.
3	Load centre	*Load_centre*	Kathmandu Other towns Others	1 2 3	This variable pertains mainly to the availability and consumption of grid electricity. Kathmandu is the capital city with a very high population density and large electricity coverage. Other towns have relatively lesser residents and smaller electricity consumption. While the remaining areas are not important from the electricity viewpoint
4	Gender	*Gender*	Female Male	1 2	These are obvious natural categories.
5	Age	*Age*	20-35 years 35-50 years > 50 years	1 2 3	This is not the age of the household head. Rather it is the age of the people who are more aware of the energy related aspects within the household. The first group (Code 1) represents the young people including students and early career professionals. Similarly, the second category is representative of mid-aged people who have a relatively stable career and are mature enough to make household decisions. The third category refers to the retired or people who work less compared to the other two classes.
6	Literacy status	*Literacy*	Illiterate Primary school/ informal education Secondary / high school University	1 2 3 4	These conventional categories have been chosen to identify people's level of awareness based on their education level.
7	Occupation	*Occupation*	Unemployed/ retired Farming/ livestock rearing Self-employed Academic/ government service Private organization	1 2 3 4 5	People's level of thinking, living standard and household practices differ with their economic condition which is directly related to occupation. A stable occupation allows people to make planned and sustainable household decisions whereas unemployment or unstable professions most likely lead to temporary decisions. The response of such varying categories of people have been examined through this classification.
8	Annual household income (USD)	*Income*	< 692 692 – 1,154 1,154 – 1,960 > 1,960	1 2 3 4	The thresholds adopted here for the annual income correspond to the World Bank's three values of the international poverty line, that of lower middle-income countries and upper middle-income countries. Annual value of NRs 90,000 is equivalent to US$ 692 per year and US$ 1.90 per day; NRs 150,000 is equivalent to US$1,154 per year and US$3.20 per day; and NRs 255,000 is equivalent to US$ 1,960 per year and US$5.50 per day using the conversion rate of US$ 1 ≈ NRs 130 during the time this research was designed.
9	Ethnicity	*Ethnicity*	Brahmin/ Chhetri Indigenous Marginalized/ Underprivileged	1 2 3	These three classes are representative of the caste/ethnicity system in Nepal which follows a privileged, indigenous and underprivileged hierarchy. Access to amenities, services and information varies significantly across these classes.
10	Household family size	*Family_size*	Nuclear (≤4 members) Extended (4-6 members) Joint (> 6 members)	1 2 3	While extended family type (including grandparents) is commonly found in semi-urban and rural areas, nuclear family has started to become the most common type in the urban areas. There are still joint families including grandparents, uncles, aunts, nephews and nieces living in the same house, mostly in the rural and remote areas.
11	Major source of household energy	*Major_energy_source*	Firewood/ dung/ agriculture residue Petroleum (kerosene) Liquified petroleum gas (LPG) Grid-electricity Renewables	1 2 3 4 5	These categories are the most common type of fuels used in Nepalese households. Their availability, prices, environmental and health impacts and people's preferences largely vary across the households using different types of energy sources.
12	Second major source of household energy	*Second_major_energy*	Petroleum (kerosene) Liquified petroleum gas (LPG) Grid-electricity Renewables	1 2 3 4	These categories are the most common type of fuels used in Nepalese households. Their availability, prices, environmental and health impacts and people's preferences largely vary across the households using different types of energy sources.
13	Vehicle ownership	*Vehicle*	No Yes	1 2	This variable has been included in our analysis to see whether having a vehicle either running on petroleum or electricity has an impact on the response of the people.

(*continued on next page*)

Table B1 (*continued*)

S. N	Variables	Given name	Classes	Code	Justification
14	Self assessment of current energy usage	*Self_assessment*	Agree Neutral Disagree	1 2 3	This acts as a triangulating variable in which people judge their activities related to energy at the household level themselves in order to provide a logical connection to their response.
Response variable					
1	People's perception of security of current household energy condition	*Perception*	Agree Neutral Disagree	1 2 3	The security of current energy condition is inclusive of available energy sources as well as the consumption pattern of the household.

Annex C: Details of the adopted ML models

1. **K-Nearest Neighbors (KNN)** works on the principle of similarity or proximity. It assumes that similar instances or data points tend to exist in close proximity in the feature space. The algorithm makes predictions by comparing the new instance to be classified with its k nearest neighbors and assigns it the majority class label among those neighbors. The value of k is a hyperparameter that needs to be defined before applying the KNN algorithm. It influences the performance and decision boundary of the model. A larger k value considers more neighbors, potentially resulting in smoother decision boundaries but may also introduce more bias. A smaller k value may lead to more localized decision boundaries but may be more sensitive to noise [112].
2. **Multi-Layer Perceptron (MLP)** consists of interconnected layers of nodes called neurons. The mathematical representation involves defining the input and output layers, assigning weights to the connections between neurons, and applying activation functions for non-linearity. Forward propagation is performed to calculate the output of each neuron, followed by an activation function at the output layer. A suitable loss function is chosen to measure the difference between predicted and true labels. Backpropagation is used to adjust the weights of the network using gradient descent optimization. This process is repeated for a number of epochs until convergence. Finally, the trained model is used to make predictions by applying forward propagation and determining the predicted labels based on output probabilities. The specific details such as the number of layers, neurons, activation functions, and optimization algorithm depend on the specific problem and dataset [109].
3. **Extra Trees Classifier (ETC)** is an ensemble learning method where multiple decision trees are trained on different subsets of the training data and their predictions are combined to make final predictions. ETC differs from Random Forest in that it selects random subsets of features at each split, leading to further diversity and potentially increased generalization performance. The algorithm assigns importance scores to features based on their ability to improve prediction accuracy. In multi-label classification, ETC can be applied by using a binary relevance approach, treating each label as a separate binary classification task. The final predictions for the multi-label classification problem can be obtained by combining the predictions from each binary classifier associated with the individual labels [123].
4. **Random Forest (RF)** is a popular ensemble learning algorithm that combines multiple decision trees to solve classification tasks, including multi-label classification. In RF, each decision tree is trained on a randomly sampled subset of the training data, and the final prediction is determined by aggregating the predictions of all individual trees. For multi-label classification, RF can be applied using a binary relevance approach, treating each label as a separate binary classification task. The algorithm constructs decision trees by recursively partitioning the feature space based on splitting criteria (e.g., Gini impurity or entropy). The feature importance in RF can be quantified using metrics such as mean decrease impurity or mean decrease accuracy. These metrics assess the contribution of each feature in reducing the impurity or improving the accuracy of the predictions. The final predictions for the multi-label classification problem are obtained by combining the predictions of the individual binary classifiers associated with each label [111].
5. **Ridge Classifier (RC)** is a linear classifier that can be used for multilabel classification tasks. It is based on Ridge Regression, which is a linear regression model regularized with L2-norm penalty. RC extends this concept to the classification setting by applying a thresholding function to the continuous output of Ridge Regression. The mathematical representation of RC involves finding the coefficients that minimize the sum of squared errors subject to the L2-norm penalty. The cost function or loss function to be optimized for RC can be expressed as:

$$\mathrm{arg}min_{\beta_0,\beta}\left\{\frac{1}{N}\sum_{i=1}^{N}\left(y_i-\beta_0-\sum_{j=1}^{p}x_{ij}\beta_j\right)^2\right\}+\gamma\sum_{j=1}^{p}\beta_j^2$$

where, N is the sample size, xi is a p-dimensional vector of features and each yi is the associated response variable, βj is the regression weights and β0 is the intercept (bias) term, γ is the regularization coefficient.

The coefficients of the cost function are determined by the following closed form solution

$$\beta=\left(X^TX+\gamma I\right)^{-1}X^TY$$

Where, X and Y are the features and associated response respectively.

The output of RC is obtained by applying a thresholding function, such as the sign function, to the linear combination of the features and coefficients. The regularization term helps control the complexity of the model and prevent overfitting. For multilabel classification, RC can be applied independently to each label, treating it as a separate binary classification task. The coefficients obtained for each label represent the importance of the corresponding features in predicting that particular label [110].

6. **Multinomial Regression – Logit (MR-L)**: The logit model is a type of regression analysis used to model the probability of a binary outcome. Like logistic regression, the logit model assumes that the relationship between the dependent variable and the independent variables is linear on the logit scale. However, the logit model is often used in econometrics, and it assumes that the error term follows a logistic distribution.

7. **Multinomial Regression – Probit (MR-P)**: The probit model is also used to model the probability of a binary outcome, but it assumes that the error term follows a normal distribution instead of a logistic distribution. The relationship between the dependent variable and the independent variables is also linear, but it is transformed using the cumulative distribution function of a normal distribution instead of the logit function. The probit model is commonly used in finance and economics.

Annex D: Some interesting responses from the survey participants

D1: A housewife from a rural municipality (Laxminiya Gaunpalika, Ward no. 6, Dhanusha district) explained during our field survey that 'guitha' is the only convenient option available to her family for cooking and sometimes heating too. They rear cows and buffalos and so the dung gets utilized as fuel free of cost. Interestingly, she expressed her dissatisfaction over people complaining of health issues due to burning 'guitha' these days and argued that they have been cooking in 'guita' since ages without such complaints. Reluctance to switch to other alternatives of cooking was clearly visible in her response. She further mentioned that efforts to introduce alternatives like LPG stoves have been met with resistance in the past due to affordability issues. The whole village reverted to 'guitha' from LPG because it was beyond what they could afford (~USD19 per 15 kg cylinder) which would hardly last a month. Interestingly, she mentioned that food cooked in the conventional way is much tastier than LPG stoves.

D2: A graduate in environmental science from Lalitpur Metropolitan (Ward no. 18), Lalitpur District admitted she did not know that domestic sector was the largest energy-consumer of Nepal. She further mentioned that the general people (including herself) would not be able to completely rely on renewables for HH energy because these new technologies are expensive.

D3: A university-educated self-employed resident of Lalitpur Metropolitan (Ward no. 16) informed us that his family is used to cooking in LPG gas stoves for more than a decade now. He feels that LPG is convenient to use, does not cause odour or smoke, and the gas cylinders are readily available for refilling. Moreover, his family is reluctant to depend completely on (electric) inductions cooktops because of the 'loadshedding' (a term used to denote scheduled power cuts in Nepal) problem. He even raised concerns over why the country can generate sufficient electricity in the monsoon but not in the dry season.

D4: A rural farmer from Besisahar Ward no. 2, Lamjung district expressed his dissatisfaction over the installation of electricity transmission towers of low height in his village which obstructed other activities such as construction of houses and roads. The villagers felt that the transmission lines and towers were built in an unplanned manner. More importantly, he pointed out that the (local) government should have involved them (the stakeholders) while designing these projects. But the villagers came to know about the project only after the towers were constructed. He further mentioned that no authority is ready to register or listen to their complaints now. These issues have eroded trust in government activities among the general population.

D5: A respondent from Nagarjun Municipality Ward no.2, Kathmandu district felt that he learned many new things about the energy sector of Nepal by interacting with our survey team. However, he expressed his dissatisfaction over the government in failing to inform the local people who are the actual energy consumers and to build trust in the new energy technologies.

D6: Another resident of Banepa Municipality Ward no.1, Kavrepalanchowk district expressed his lack of awareness of renewable energy technologies particularly regarding those that are applicable to the general people at the HHs level. However, based on how much he knew, he was positive about switching to clean energy for the sake of a better and sustainable future.

D7: A schoolteacher from Khairahan Gaupalika Ward no.8, Chitwan district felt that awareness about the benefits of renewable energy technologies for Nepal should be included in the school curriculum. Moreover, he stressed that enough subsidies need to be provided to actually implement renewable energy technologies in the community as individuals will not be able to afford such a transformation on their own.

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