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Developing a SmartSoil Classifier Tool for Classifying Soils According to Soil Taxonomy at Subgroup level for Some Soils in Iraqi Alluvial Plain Using Python

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ABSTRACT: A software tool was developed in Python to automate soil classification according to Soil Taxonomy (1999) and Keys to Soil Taxonomy (2022) for the Entisols and Aridisols orders, down to the most common Subgroups in Iraqi Alluvial Plain. The reference database was used of 309 Pedons from four previously studied projects Sheikh Saad, Najmi, Awadiyat, and Shataniyah. These Pedons were classified by experts to evaluate the performance of the developed software. Three areas were selected for field soil surveys: Sheikh Saad, Al-Warkaa, and Al-Islah, encompassing 18 Pedons and 47 boreholes, with a total area of 12,317 hectares. The program's performance evaluation results, when compared with expert classifications, showed an overall accuracy of 93.5% at the order level. At the sub-order level, the accuracy was 89.32%, while the overall accuracy at the Great group level was 78.96%. At the sub-group level, the overall accuracy was 70.55%. Analysis of variance revealed 14 categories of discrepancies, most of which stemmed from errors in reference data and human estimation. After correcting these errors, the classification accuracy theoretically reached 100%. When the field results for the described 18 Pedon's, distributed across three governorates within the Iraqi alluvial plain, were presented, the program's performance evaluation results showed 100% accuracy across all classification levels. This reflects the program's ability to process field and laboratory data. However, this accuracy remains dependent on the quality of the morphological description, as results may be affected if the person describing the pedon changes, particularly in criteria that rely on estimation, such as waterlogging conditions.

INTRODUCTION:

Soil is a natural system characterized by variations in its physical and chemical properties both spatially and temporally, resulting from the continuous interaction of soil-forming factors. These properties are subject to a system of interconnected relationships, where any change in one property influences the variation in others. This necessitates conducting precise soil surveys and classifications to study soil formation mechanisms and understand its geographical distribution (Demattê *et al.,* 2025). This in-depth understanding is fundamental to protecting this natural resource and ensuring its sustainability.

Since the variation in soil properties and characteristics is the standard for identifying and classifying soil types, soil classification has become essential. The history of soil classification has undergone transformations, starting from morphological descriptions and farmers' inherited experiences to international classification systems, such as the Soil Taxonomy system, which is based on quantitative criteria and diagnostic perspectives (USDA, 1975). The qualitative development of this system has led to increased accuracy in isolating similar soils through a hierarchical system that begins with order as the highest classification level and descends to lower classification levels represented by series and phase (USDA, 1999). However, this development has resulted in structural and conceptual ambiguity, which has become an obstacle in identifying and classifying taxonomic units and has led to the emergence of gray areas characterized by taxonomic ambiguity and overlapping boundaries between diagnostic horizons. This necessitates a shift towards more capable tools for addressing these statistical and morphological overlaps, one of which is the automation of the soil classification process. By employing the Python programming language, data is treated as inputs subjected to systems that simulate the mind of an expert classifier.

The automation of soil classification processes using programming languages has witnessed an evolutionary journey, as those initial models focused on simulating classification keys and converting them from their paper textual form to linear programming algorithms. This began with the attempt of Fisher and Balachandran (1989), who developed the STAX system, which was based on the Turbo Prolog language. At the time, it represented a qualitative leap in the methodology of dealing with pedological data. The system was based on building procedural logical trees that depend in essence on a series of interactions with the user through binary "yes" or "no" answers to gradually reach the level of classification orders, provided that there is a prior determination of the diagnostic features. This scientific journey then continued to develop with the model presented by Buol and Rebertus (1991). This coincided with a similar system developed by Galbraith *et al*., (1998a), which provided solutions to address the problem of missing data that hindered the classification of certain complex orders such as Histosols and Spodosols. Automation then moved to a more mature stage with the work of Galbraith (1996) and Galbraith *et al*., (1998b), as they developed a prototype of the expert system that was characterized by the ability to estimate diagnostic features and use expert alternatives to deal with missing data. Software packages in the R language such as AQP contributed to the standardization of pedometer criteria, which Heuvelink (2003) defined as the application of mathematical methods to study soil origination. The Web Soil Survey tool has successfully achieved high classification accuracy for classes such as Histosols, Spodosols, Andisols, and Oxisols. This success followed the launch of web-based soil surveying, which paved the way for modern computer systems that revolutionized soil data access and processing. Building on this technological advancement, Beaudette and O'Geen (2009) simplified the presentation of this data, providing detailed graphs of key characteristics and linking pedon data to advanced digital tools like Google Earth, thus facilitating data retrieval and accurate analysis. This leads to the tool developed by Olds (2022), which encompasses all taxonomic orders and suborders within a single R programming framework.

Python is one of the most important programming languages used in scientific research due to its simplicity and power in handling artificial intelligence and data analysis, thanks to libraries like Pandas and NumPy. It also plays a vital role in developing machine learning algorithms through libraries like TensorFlow and PyTorch, making it an indispensable tool in academic and research settings for conducting complex computational experiments (TIOBE, 2023).

The reliance on automated techniques in soil science has increased since the Beaudette *et al*., (2013) study, which facilitated access to global databases. This was followed by semi-automated methodologies to improve the accuracy of digital soil maps using the Random Forests algorithm, as demonstrated by Nauman and Thompson (2014). In the same year, Bockheim *et al*., (2014) used Python to classify Antarctic soils. Hartemink and Minasny (2015) introduced the concept of digital morphological soil measurement. This evolved into the production of comprehensive predictive maps with models such as Chen and Rodriguez (2016), which achieved 89.5% accuracy, and the SoilPyClass tool by Tanaka and Ibrahim (2017), culminating in the production of global maps by Hengl *et al*., (2017) with 99.3% accuracy. Furthermore, Velamala and Pant (2025) developed the open-source software tool PySNM using Python to automate the spatial distribution of nutrient by IDW and generate nutrient maps (N, P, K, pH). This tool has proven highly efficient in map production, outperforming traditional software such as ArcMap.

RESEARCH METHODOLOGY:

The field procedures included selecting three distinct areas within the Iraqi alluvial plain, influenced by the flood deposits of the Tigris and Euphrates rivers and the adjacent marshes. These areas were studied, and available data was collected. Field soil surveys were conducted in the following locations: the first, the Sheikh Saad area (4677.4 hectares) in Wasit Governorate; the second, the Warka area (13753 hectares) in Muthanna Governorate; and the third, the Al-Islah area (16810 hectares) in Dhi Qar Governorate. A semi-detailed field survey was conducted using 18 buckets and 47 boreholes.

The desk procedures included analyzing the data obtained in the field, as well as designing the SmartSoil Classifier program for soil classification, which represents the outcome of this study, and comparing the results obtained from the program with the field data, as well as comparing them with a reference database of four previously studied and documented soil survey projects, namely the Sheikh Saad project in Wasit Governorate, the Imtidad Al-Najmi project in Al-Muthanna Governorate, and the Al-

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Awadiyat and Al-Shataniyah projects in Dhi Qar Governorate. The SmartSoil Classifier V1.0 tool was programmed as part of the Soil Taxonomy suite in Python 3.11+ with a graphical interface built on the PyQt5 framework. This enables the processing of soil pedons data. The tool was developed with a modifiable and scalable architecture. The input system relies on three main data files in Excel format. These files form the data framework and contain all quantitative laboratory and field data. The first file is populated with soil salinity data obtained from laboratory results, as shown in Figure (1), and the salinity values are entered in

dSm^{-1}. The second file contains soil texture data from boreholes, also as shown in Figure (1), and soil texture data is populated here as well. The third file contains information about the pedons obtained in the field and laboratory, as shown in Figure (2). The study involved 27 variables, including Electrical conductivity data in dSm^{-1}, the percentage (%) of soil particles (clay, silt, and sand), gypsum content, lime content, SAR, ESP, and Calcium, Magnesium, Sodium, Potassium, Chlorides, Sulfates, Carbonates, and Nitrates in $meqL^{-1}$. Other variables included drainage conditions, soil cracks, and the geographic location.

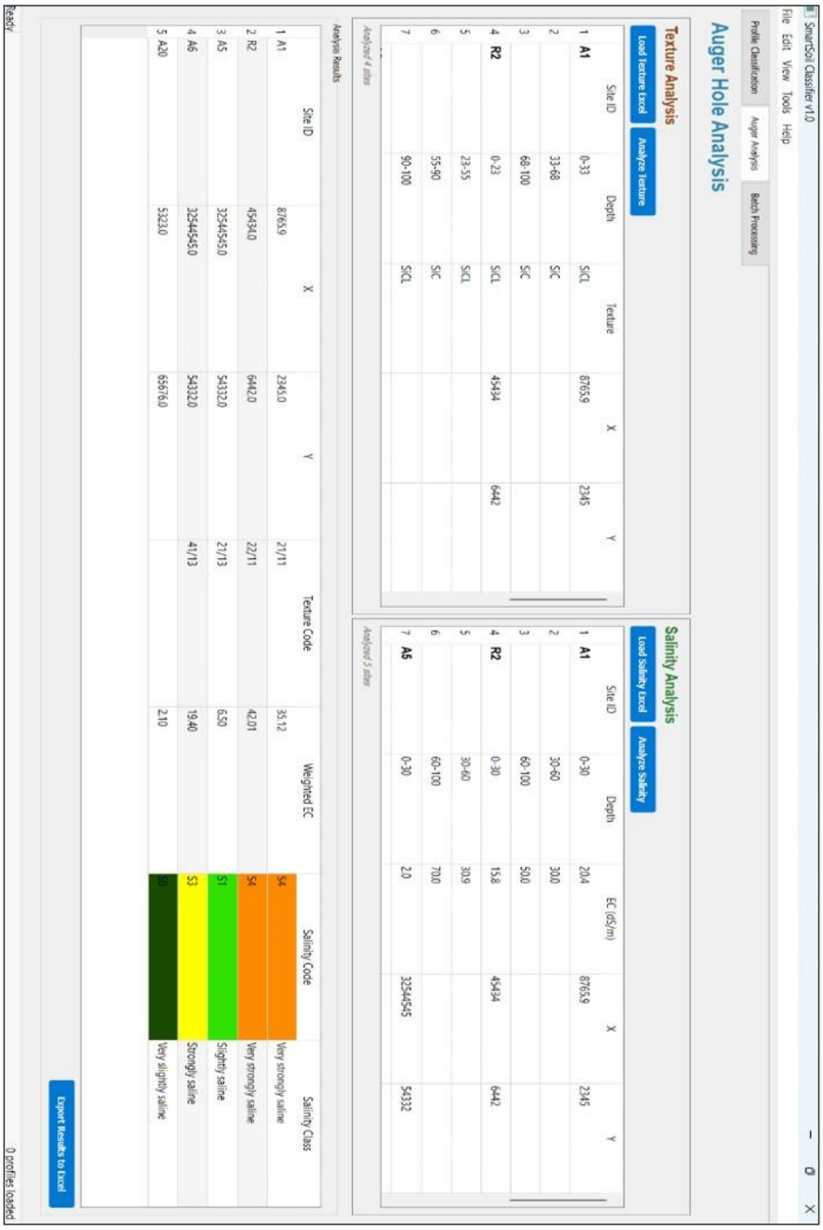

Figure (1) Data entry and results for Auger holes

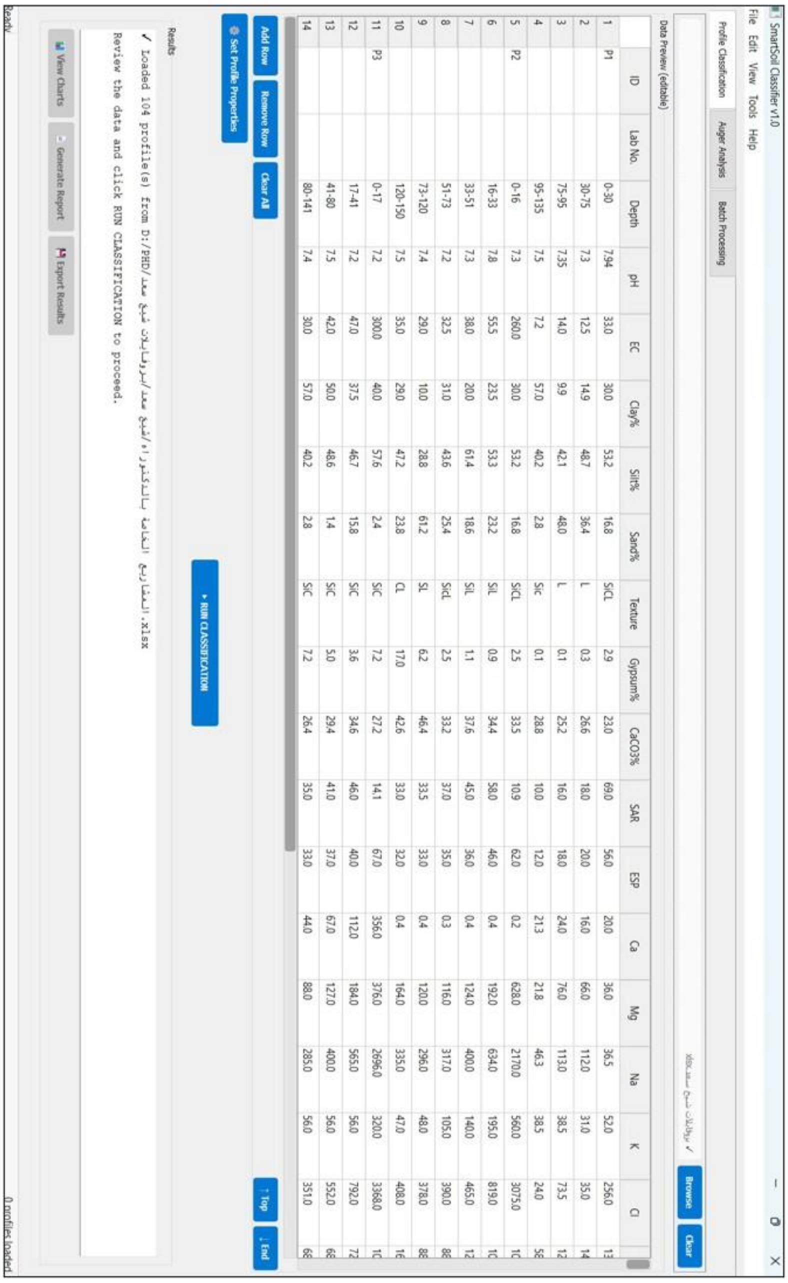

Figure (2) Data entry and results for Pedons

Processing Operations:

The structure of SmartSoil Classifier V1.0 system relies on activating classification algorithms during program execution via the Run Classification and Analyze Salinity, Texture icons. It offers flexibility in running the classification path for boreholes or pedons individually or in combination, according to study requirements. The outputs of logical and arithmetic operations are automatically transferred to specialized Excel files and exported via the Export results icon, whether for drill hole results or borehole results.

The file generated from the boreholes salinity analysis stores the results of the weighted average soil salinity and classifies it into six categories, from S0 (Very slightly saline) to S5 (Extremely saline), according to S.O.L.R. (1982), as shown in Table (1). The other part of the process involves classifying the soil texture of the first meter according to the S.O.L.R. (1982) system (Table

2). This classifies the soil into four categories, with the first meter representing the soil texture as a fraction. The numerator represents the depths (25-0) and (50-25), and the denominator represents the layers (75-50) and (100-75).

Meanwhile, the data file presents the final results of the soil classification based on the hierarchical decision tree algorithm. This algorithm transforms descriptive and quantitative criteria into decision matrices governed by numerical thresholds, in accordance with soil taxonomy parameters. This classification relies on the integration of physical parameters such as the distribution of soil particles sand, silt, and clay, surface cracking, and chemical parameters such as electrical conductivity, pH, gypsum content, and calcium carbonate. It also incorporates morphological characteristics, including the thickness of the diagnostic horizons, drainage conditions. The program performs classification through a series of diagnostic tests, including the detection of saline, gypsum, and calcareous horizons.

The program also evaluates some derived properties for each soil sample, namely the weighted average of electrical conductivity, which is classified according to S.O.L.R. (1982) in Table (1). It classifies the soil texture at the family level based on the weighted average of the size distribution of soil particles (excluding the top 25 cm) according to the USDA's family-level soil texture triangle classifications, as shown in Table (3). It calculates the weighted average of the soil pH and classifies it according to the USDA's (2024). It isolates the surface soil texture and then classifies it according to S.O.L.R. (1982) for texture in Table (2) for inclusion in the Phase. Finally, it characterizes the diagnostic horizons.

Table (1) Soil Salinity Classification according to S.O.L.R. 1982)

Class	Degree of Salinity	Electro-conductivity of soil saturated extract ECe at T = 25°C $dS.m^{-1}$
S0	Very slightly saline soil	0 – 4
S1	Slightly saline soil	4 – 8
S2	Moderately Saline soil	8 – 16
S3	Strongly Saline soil	16 – 25
S4	Very strongly saline soil	25 – 50
S5	Extremely saline soil	> 50

Table (2) Soil texture classes according to (S.O.L.R, 1982)

Soil texture symbol	Group symbol	Soil texture category
C, SiC, SC	1	Fine textured soil
CL, SiCL, SCL	2	Moderately fine textured soil
Si, L, SiL, SL	3	Medium textured soil
S, LS	4	Coarse textured soil

Table (3) Soil separator values and triangular tissue classes by family (USDA, 1999)

Class	Clay %	Silt %	Sand %
Very fine	≥ 60%	-	-
Fine	35–60%	-	-
Fine silty	18–35%	-	≤ 15%

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Fine loamy	18–35%	-	> 15%
Coarse silty	< 18%	-	≤ 15%
Coarse loamy	< 18%	Silt + 2×Clay ≥ 30%	-
Sandy	< 18%	Silt + 2×Clay < 30%	-

RESULTS AND DISCUSSION:

Verification with Expert Data:

Since the classification is hierarchical, the results are presented sequentially, starting with Order, then Sub-Order, Great Group, and Sub-Group. Discussions are limited to the Sub-Group level, as it forms the basis of the classification.

Order:

Figure (3) illustrates the classification distribution at the Order level between the data classified by experts as the standard reference and the program data as the dependent variable. The results of the comparison, conducted on 309 pedons, showed that the program correctly classified 240 out of 248 pedons as Aridisols and 49 out of 61 pedons as Entisols.

The program demonstrated an accuracy rate of 96.7% in classifying Aridisols, making only eight errors out of 248. Its accuracy in classifying Entisols was 80.3%. The results also indicated that the overall accuracy of the program in classification reached 93.5%, which was calculated according to the following equation:

Overall Accuracy = (Sum of Correct Predictions / Sum of Total Predictions) × 100 … (1)

= (289/309) × 100

Overall Accuracy = 93.5%.

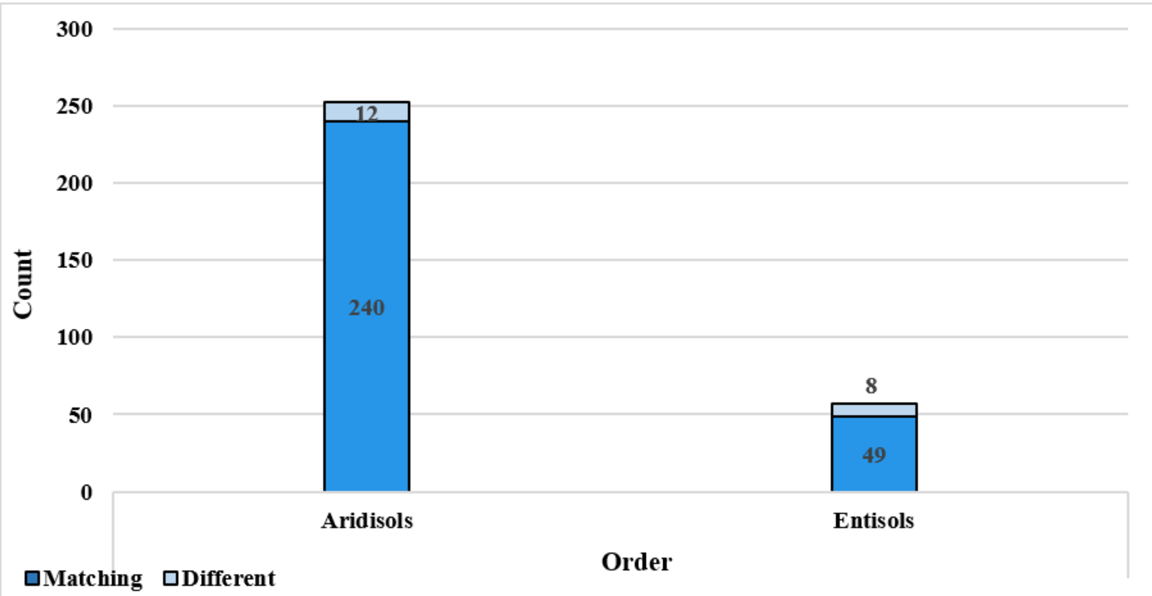

Figure (3) Classification Distribution between Matches and Mismatches in Classification at Order Level

Suborder:

At the suborder level, the following suborders were classified: Salids, Gypsids, Calcids, Psamments, and Fluvents. Figure (4) illustrates the results of the comparison between the expert classification, which represents the baseline, and the program classification.

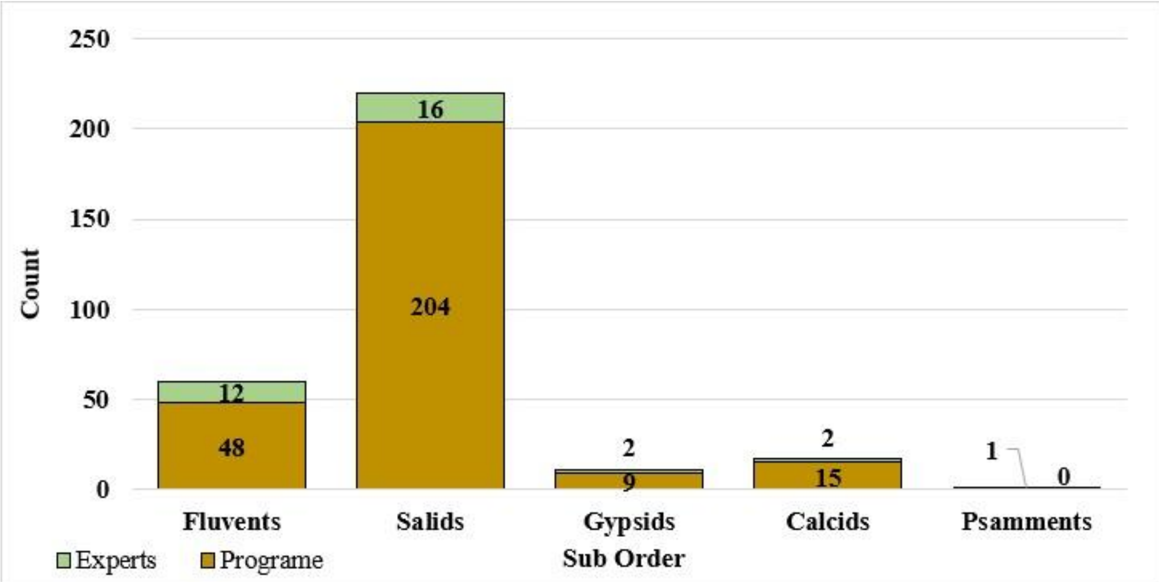

Figure (4) Contrast between the data classified by the experts and the program's results at the Suborder level

The results showed that the overall accuracy of the program in classifying soils at the Suborder level was 89.32%. It failed to classify the Psamments Suborder, even though it was the only pedon described by the experts as belonging to this Suborder. However, it achieved an 80% accuracy rate in classifying the Fluvents Suborder and successfully classified 48 out of 60 pedons within this Suborder. The program correctly classified 204 out of 220 pedons, achieving a 92.7% success rate for the Salids Suborder. For the Gypsids Suborder, it correctly classified 9 out of 11 pedons, achieving an 81.8% success rate. For the Calcids Suborder, the program correctly classified 15 out of 17 pedons, achieving an 88.2% success rate.

Great Soil Group:

The comparison results in Table (4), which represents the Confusion Matrix between the expert classification (the baseline) and the program classification, show that the overall classification accuracy at Subgroup was 78.96%. Specifically, it correctly classified the Torrifluvents Subgroup at 80%, Aquisalids at 67%, Haplosalids at 87.6%, Haplogypsids at 90%, and Haplocalcids at 78.6%.

Table (4) Confusion Matrix between the expert classification data and the program results at the Great soil group

Confusion matrix		Programme					
		Torrifluvents	Aquisalids	Haplosalids	Haplogypsids	Haplocalcids	Total
Experts	Torripsamments	2					2
	Torrifluvents	48		5	4	3	60
	Aquisalids	2	63	24	2	3	94
	Haplosalids	2	3	113	3	8	129

	Haplogypsids	1			9		10
	Haplocalcids	2		1		11	14
	Total	57	66	143	18	25	309

Subgroup:

The results indicate that the program, when classifying 309 pedons at the Subgroup, correctly classified 223 pedons and incorrectly classified 86 (Table 5), resulting in an overall accuracy of 70.55%. Regarding the classification of the Typic Torrifluvents Subgroup, the program successfully classified 33 out of 40 pedons, achieving an accuracy of 82.5%. The program also achieved 100% success in classifying the Aquic Haplocalcids Subgroup, correctly classifying all 12 pedons. This is attributed to the clarity of the Calcids horizon conditions and the distinct characteristics of Aquic, determined by the staining patterns, depth, color clarity, and quantity. The program correctly classified 19 out of 21 pedons identified by experts as Gypsic Aquisalids, achieving an accuracy of 90.5%. This reflects its high ability to distinguish both the Gypsids horizon and Aquisalids conditions. The program also successfully classified 32 out of 36 pedons with an accuracy of 88.9%, increasing its reliability in classifying soils, whether they contain saline or gypsum horizons. The program also demonstrated accuracy in classifying soils within the Typic Haplosalids Subgroup, successfully classifying 51 out of 64 pedons with a classification accuracy of 79.7%. It correctly classified one pedon out of one with 100% accuracy in classifying soils within the Typic Haplogypsid Subgroup. Its accuracy was somewhat lower, at 75.4%, when classifying these soils within the Typic Aquisalids Subgroup, successfully classifying 43 out of 57 pedons. The program also successfully identified 7 out of 14 pedons within the Calcic Aquisalids Suborder with an accuracy of 50%. It also correctly classified 10 out of 15 pedons within the Aquic Torrifluvents Subgroup, with an accuracy of only 66.7%. Its accuracy was also low in identifying the Calcic Haplosalids Subgroup, correctly identifying 10 out of 21 pedons, resulting in an accuracy of 47.6%. Its accuracy dropped to 30% when identifying the Typic Calcigypsids Subgroup, successfully classifying only 3 out of 10 pedons. The program correctly classified only two pedons, one of which was classified within the Leptic Haplologypsids Subgroup, while experts did not classify any pedons within this Subgroup. The program failed to classify any of the pedons classified by experts under the following subgroups: Sodic Haplocalcids, Sodic Haplosalids, Vertic Torrifluvents, Vertic Haplocalcids, and Typic Torripsamments, achieving an accuracy of 0%.

Table (5) Confusion Matrix between Expert-Classified Data and Program Results at the Subgroup Level

Confusion matrix		**Program**															
		Vertic Torrifluvents	Aquic Torrifluvents	Typic Torrifluvents	Gypsic Aquisalids	Calcic Aquisalids	Typic Aquisalids	Gypsic Haplosalids	Calcic Haplosalids	Typic Haplosalids	Leptic Haplogypsids	Typic Haplogypsids	Typic Calcigypsids	Aquic Haplocalcids	Typic Haplocalcids	Vertic Haplocalcids	Total
Eperts	Typic Torripsamments			2													2
	Vertic Torrifluvents			3													3
	Aquic Torrifluvents	1	10							1		2		1			15
	Typic Torrifluvents	1		33					1	3			2		2		42

	Gypsic Aquisalids				19		1						1				21
	Calcic Aquisalids				6	7						1					14
	Typic Aquisalids		2		3	6	43			1				2			57
	Gypsic Haplosalids							33		1		2					36
	Calcic Haplosalids							1	10	9					1		21
	Typic Haplosalids			1			1	2	10	51					1		66
	Typic Haplogypsids										1						1
	Typic Calcigypsids			1							2	3	3			1	10
	Aquic Haplocalcids													12			12
	Sodic Haplocalcids		1	1											1		3
	Sodic Haplosalids			1									1		2		4
	Typic Haplocalcids														2		2
	Total	2	13	42	28	13	45	36	21	66	3	8	7	15	9	1	309

When examining cases of classification discrepancies, an analysis of the reasons for the discrepancies was conducted by reviewing laboratory results and the morphological descriptions of the pedons included in the reference reports. It should be noted that this analysis was not intended as a critique, but rather to understand the nature of the interaction between human assessment, digital systems, and machine learning. When these cases were subjected to the rules of the Soil Taxonomy system, the program demonstrated that it produced classifications characterized by accuracy and conformity to the classification criteria. In some cases, the program showed an ability to adhere to classification standards and boundaries that might be subject to relative judgment during traditional expert review of soil survey reports.

Table (6) illustrates the discrepancies between the expert classification and the program classification for some pedons in the Sheikh Saad, Al-Awadiyat, Al-Najmi, and Al-Shataniyah projects, categorizing them into 14 categories for discrepancies reasons. This is attributed to variations in the interpretation of the soil diagnostic characteristics. Three Pedons were initially classified as Sodic Haplocalcids despite their pH values not exceeding the limits required for sodic soils. Furthermore, the Calcic horizon criteria were not met in some locations, leading to their reclassification as Typical Haplocalcids or Torrifluvents, depending on the availability of diagnostic horizons. Errors were also observed in the application of the classification precedence principle. Vertic criteria were met in some Pedons, such as P23 and P43, necessitating their classification as Vertic Torrifluvents, while other Pedons were classified in this Subgroup despite not meeting the criteria. Additionally, the Aquic criteria were misinterpreted in some cases due to a lack of spotting, while in others, they were disregarded despite being met. The results also showed that the Psamments criteria were not met in some Pedons due to a lower than required sand content, resulting in their reclassification as Torrifluvents. Errors were also found in determining the sequence of the Calcic and Gypsic horizons. In some cases, the condition of having a calcic horizon above the gypsic horizon was not met, while in others, the gypsic or calcic horizons were neglected despite meeting the laboratory criteria. Errors were also found in assuming the presence of a salic horizon in some pedons without meeting its criteria, while its presence was neglected in others, changing their classification from Entisols to Aridisols. The presence of gypsum at shallow depths also showed an effect in some pedons, necessitating the inclusion of the Leptic characteristic in their classification. In general, the differences between the expert classification and the program classification are due to misinterpretation of diagnostic characteristics, failure to meet the criteria for some horizons, neglect of the principle of taxonomic priority, and inaccurate reliance on morphological description without full verification of laboratory results. This is reflected in the different classifications shown in Table (6).

Table 6: Comparison between the expert classification, the program classification, and Pedon numbers.

Project	Pedon No.	Experts	Program	Mismatch Reason
Shik Saad	P22	Sodic Haplocalcids	Typic Haplocalcids	pH
	P46	Sodic Haplocalcids	Aquic Torrifluvents	
	P78	Sodic Haplocalcids	Typic Torrifluvents	
Shik Saad	P6	Sodic Haplosalids	Typic Calcigypsids	No classification by this name
	P18, P28	Sodic Haplosalids	Typic Haplocalcids	
	P83	Sodic Haplosalids	Typic Torrifluvents	
Awadiyat	P23	Typic Torrifluvents	Vertic Torrifluvents	Vertic criteria met
	P43	Aquic Torrifluvents	Vertic Torrifluvents	
Shataniya	P29, P76	Vertic Torrifluvents	Typic Torrifluvents	Vertic criteria not met
Najmi	P5	Vertic Torrifluvents	Typic Torrifluvents	
Awadiyat	P57	Typic Aquisalids	Typic Haplosalids	Aquic conditions
	P76	Typic Haplosalids	Typic Aquisalids	
Awadiyat	P41	Typic Torripsamments	Typic Torrifluvents	Psamments criteria not met
Shataniya	P9	Typic Torripsamments	Typic Torrifluvents	
Shik Saad	P24, P75, P101	Typic Calcigypsids	Typic Haplogypsids	Absence of a Calcic horizon above a Gypsic
Shik Saad	P5, P17, P19, P25, P66, P67, P72, P91, P100	Calcic Haplosalids	Typic Haplosalids	Absence of a Calcic horizon
Shik Saad	P35	Gypsic Haplosalids	Typic Haplosalids	Absence of a Gypsic horizon
	P40	Gypsic Aquisalids	Typic Aquisalids	
	P68	Typic Calcigypsids	Vertic Haplocalcids	
	P89	Typic Calcigypsids	Typic Torrifluvents	
Najmi	P4	Calcic Haplosalids	Typic Haplocalcids	Absence of a Salic horizon
Shik Saad	P26	Gypsic Aquisalids	Typic Calcigypsids	
	P39, P80	Gypsic Haplosalids	Typic Haplogypsids	
	P81	Calcic Aquisalids	Typic Haplogypsids	

Project	Pedon No.	Experts	Program	Mismatch Reason
Najmi	P12	Typic Aquisalids	Aquic Torrifluvents	
Awadiyat	P5	Typic Aquisalids	Aquic Haplocalcids	
Shataniya	P6	Typic Haplosalids	Typic Torrifluvents	
	P22	Typic Haplosalids	Typic Haplocalcids	
	P36	Typic Aquisalids	Aquic Torrifluvents	
	P78	Typic Aquisalids	Aquic Haplocalcids	
Shik Saad	P4, P74	Typic Calcigypsids	Leptic Haplogypsids	Gypsic horizon within the upper 18 cm
Najmi	P17	Typic Haplogypsids	Leptic Haplogypsids	
Najmi	P3, H12	Typic Haplosalids	Calcic Haplosalids	Presence of a Calcic horizon
Awadiyat	P2	Typic Haplosalids	Calcic Haplosalids	
	P8, P20	Typic Aquisalids	Calcic Aquisalids	
	P28, P56, P81	Typic Haplosalids	Calcic Haplosalids	
	P71, P74, P79	Typic Aquisalids	Calcic Aquisalids	
Shataniya	P2	Typic Haplosalids	Calcic Haplosalids	
	P20, P26	Typic Torrifluvents	Typic Haplocalcids	
	P45	Typic Aquisalids	Calcic Aquisalids	
	P71	Aquic Torrifluvents	Aquic Haplocalcids	
	P74, P82, P83	Typic Haplosalids	Calcic Haplosalids	
Shik Saad	P57, P59	Typic Torrifluvents	Typic Calcigypsids	Presence of a Gypsic horizon
	P44, P64, P65, P71, P79, P85	Calcic Aquisalids	Gypsic Aquisalids	
	P99	Calcic Haplosalids	Gypsic Haplosalids	
Awadiyat	P29, P36, P83	Typic Aquisalids	Gypsic Aquisalids	
	P37	Aquic Torrifluvents	Typic Haplogypsids	
Shataniya	P10, P39	Typic Haplosalids	Gypsic Haplosalids	
	P50	Aquic Torrifluvents	Typic Haplogypsids	
Shik Saad	P1, P7	Typic Torrifluvents	Typic Haplosalids	Presence of a Salic horizon
Awadiyat	P1	Typic Torrifluvents	Calcic Haplosalids	
	P38	Aquic Torrifluvents	Typic Haplosalids	
	P64	Typic Torrifluvents	Typic Haplosalids	

Figure (5) illustrates mismatched of pedon numbers distributed across the Soil Taxonomy levels. Mismatches were prevalent across all levels. The most frequent category was the presence of a Calcic horizon that was not identified by experts despite laboratory confirmation, primarily affecting the Subgroup level (16 pedons) and to a lesser extent the Order level (3 pedons).

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Conversely, the category of the absence of a Calcic horizon (9 pedons) was frequently observed when experts indicated its presence without laboratory confirmation of its conditions, and its impact was limited to Subgroup. This was followed by the category of the presence of an unidentified Gypsic horizon (16 pedons), which mainly affected the Subgroup (12 pedons) and the Order (4 pedons). Finally, the category of the absence of a Gypsic horizon (4 pedons) emerged as a result of its presumed presence without the fulfillment of its conditions, and it affected the Order, Suborder, and Subgroup. The absence of a Salic horizon (11 pedons) was also a recurring issue due to misinterpretation of its criteria, leading to taxonomic changes in the Order and Suborder. Its presence was overlooked in 5 pedons despite laboratory confirmation, resulting in a change in the Order. The presence of an unrecognized classification within Soil Taxonomy, namely Sodic Haplosalids, was also observed in 5 pedons, leading to changes in the Order and Suborder. The pH values were also a recurring issue in 3 pedons due to the classification of some soils as Sodic despite unsuitable pH values, affecting the Order and Subgroup. Errors related to other morphological and diagnostic characteristics included the failure to meet Vertic criteria (3 pedons) versus meeting them without diagnosis in 2 pedons, the failure to meet the requirement of a Calcic horizon above Gypsic (3 pedons), which affected the Great group level, and the failure to meet Psamments criteria (2 pedons). The presence of a Gypsic horizon was also a recurring characteristic within the first 18 cm (3 pedons), necessitating the inclusion of the Leptic attribute and affecting the Great Group and Sub Group levels. Aquic conditions appeared in two pedons, a category heavily dependent on the expert's morphological judgment. Overall, the results indicate that the discrepancies in classification stem from key methodological factors, most notably the variation in the application of classification rules between experts and the software, in addition to the impact of ground truth data quality and its potential for individual errors. This aligns with McBratney *et al.*, (2000) observations regarding the importance of ground truth data accuracy in determining the level of taxonomic concordance.

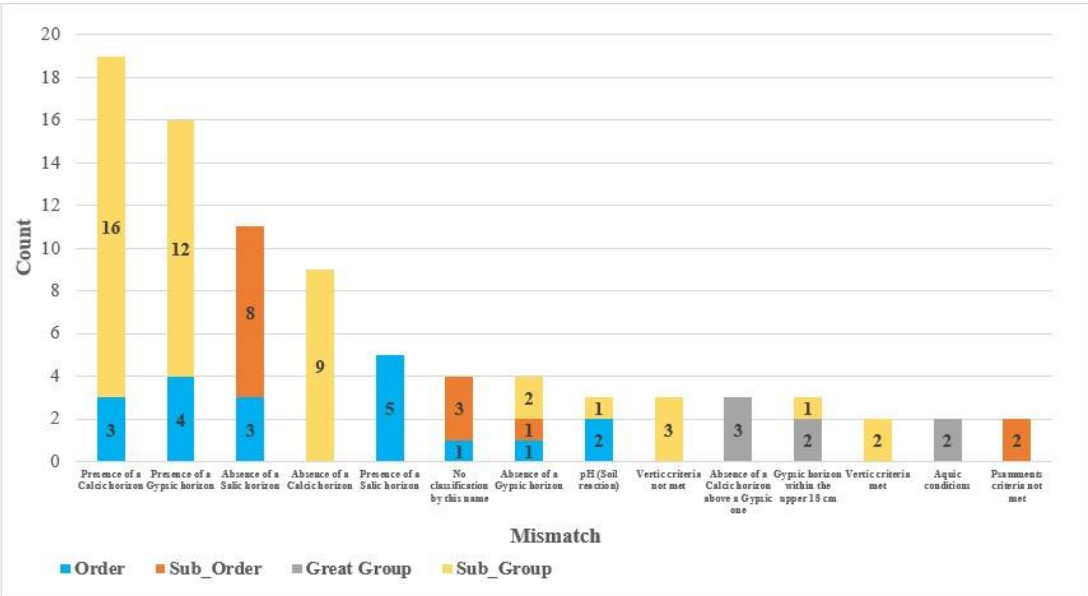

Figure (5) Number of non-concordant Pedon's across Soil Taxonomy levels

Program Accuracy Calibration:

Accordingly, recalibrating the program's accuracy after correcting these errors in the reference data indicates that the classification accuracy can theoretically reach higher levels, as shown in Table (7). This enhances the program's efficiency not only as a classification tool but also as a means of verifying maps and soil classification data, thus reducing the margin of human error in pedological studies, in addition to saving time and effort. The results in Table (7) show high accuracy for each category, reaching 100% for most categories, except for the Typical Aquisalids category, which reached 95.5%, where 43 out of 45 Pedons matched, and the Typical Haplosalids category, which reached 96.9%, where the classification of 64 out of 66 Pedons matched. The reason for this variation is attributed to the judgment made regarding the conditions of Aquisalids, as this remains unmeasurable and depends on the expert's opinion, despite the existence of evidence indicating that the presence, depth, quantity, and color of the spots are indicators for measuring this description.

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Table (7) Confusion Matrix between Expert Data and Program Results at Subgroup after Adjustments to Reference Data

Confusion matrix		Program															
		Vertic Torrifluvents	Aquic Torrifluvents	Typic Torrifluvents	Gypsic Aquisalids	Calcic Aquisalids	Typic Aquisalids	Gypsic Haplosalids	Calcic Haplosalids	Typic Haplosalids	Leptic Haplogypsids	Typic Haplogypsids	Typic Calcigypsids	Aquic Haplocalcids	Typic Haplocalcids	Vertic Haplocalcids	Total
Experts	Vertic Torrifluvents	2															2
	Aquic Torrifluvents		13														13
	Typic Torrifluvents			42													42
	Gypsic Aquisalids				28												28
	Calcic Aquisalids					13											13
	Typic Aquisalids						43			2							45
	Gypsic Haplosalids							36									36
	Calcic Haplosalids								21								21
	Typic Haplosalids						2			64							66
	Leptic Haplogypsids										3						3
	Typic Haplogypsids											8					8
	Typic Calcigypsids												7				7
	Aquic Haplocalcids													15			15
	Typic Haplocalcids														9		9
	Vertic Haplocalcids															1	1
	Total	2	13	42	28	13	45	36	21	66	3	8	7	15	9	1	309

Verification of Field Data:

To evaluate the program's performance in the second phase, a set of data collected from fieldwork, including a survey of three locations -Sheikh Saad area in Wasit Governorate, Al-Warka area in Al-Muthanna Governorate, and Al-Islah area in Dhi Qar Governorate- was used. A total of 18 pedons were classified, and the program's outputs were compared with these classifications. A confusion matrix was used to interpret the results.

Order:

Figure (6) illustrates the classification distribution between the classified data collected from the fieldwork and the program's data as a dependent variable, at the order level. The results of the comparison conducted on the 18 pedons showed that the program correctly classified the Aridisols Order in 14 out of 14 pedons and correctly classified the Entisols Order in 4 out of 4 pedons.

The results also indicated that the program's classification accuracy was 100%, which was calculated using equation (1).

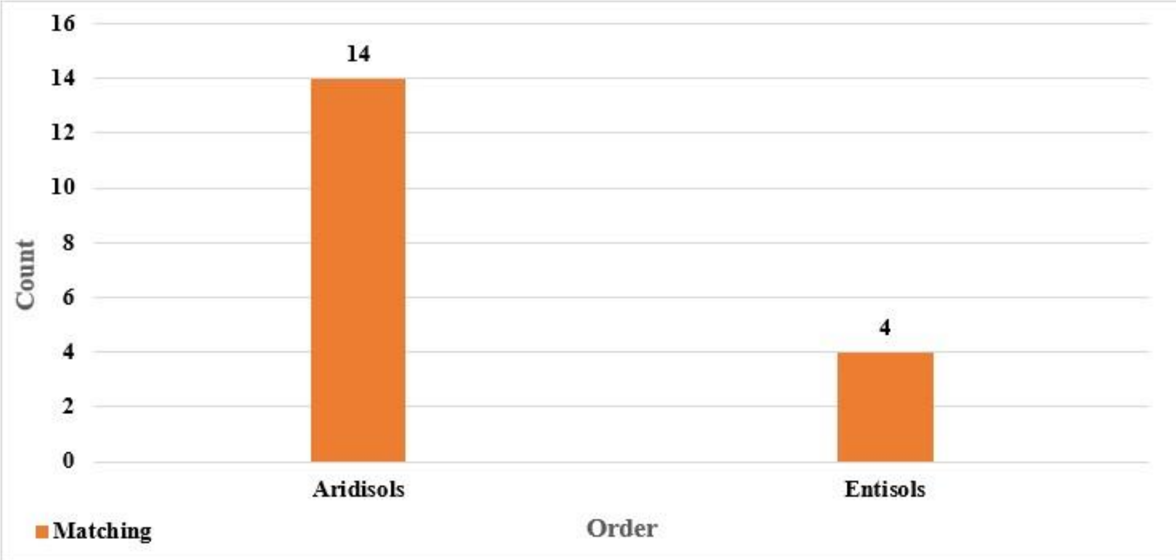

Figure (6) Classification distribution between matches and non-matches in the classification of field data at Order level

Sub-Order:

At the Suborder level, the following suborders were classified: Salids, Gypsids, Calcids, and Fluvents. Figure (7) illustrates the discrepancy in the data between the fieldwork classification, which represents the baseline, and the program classification.

The results showed that the program correctly classified the Fluvents Suborder, successfully classifying 4 out of 4 pedons within this Suborder. Regarding the Salids, Gypsids, and Calcids Suborders, the program demonstrated superior classification across all of them. It correctly classified all 7 pedons within the Salids Suborder, 2 out of 2 pedons within the Gypsids Suborder, and 5 out of 5 pedons within the Calcids Suborder. Therefore, its overall accuracy reached 100%.

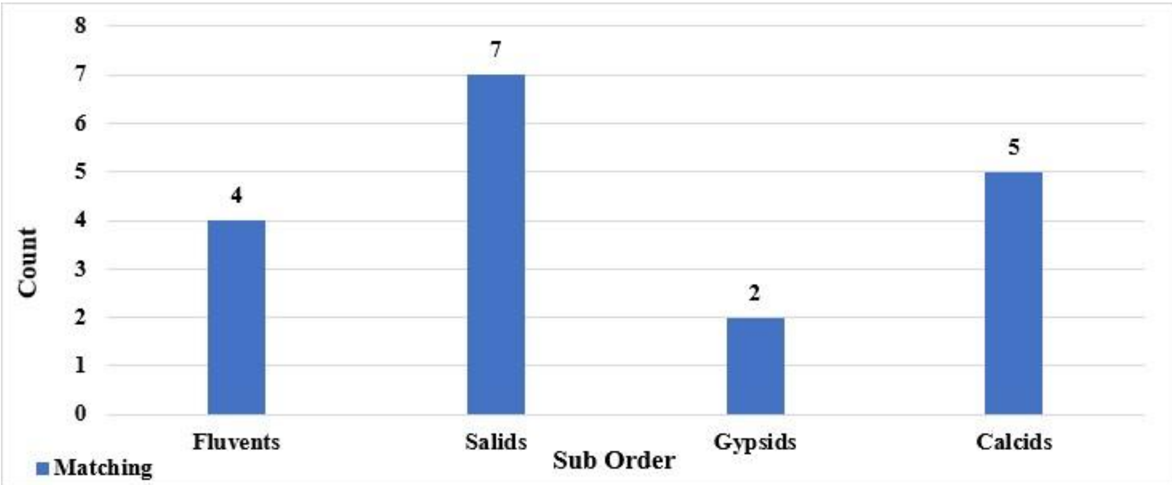

Figure (7) Confusion Matrix between Classified Field Data and Program Results at the Sub-Order Level

Great soil group:

At the Great group level, soils were classified into five Great groups: Torrifluvents, Aquisalids, Haplosalids, Haplogypsids, and Haplocalcids. The results of the comparison are presented in Table (8), which represents the Confusion Matrix between the field classification and the program classification. The results showed that the program correctly classified all four pedons within the Torrifluvents Great group. It was able to accurately classify the Aquisalids Order across all five targeted pedons. The same applies to the Haplosalids Great group, where the classification was identical at both pedons designated for this category. The same pattern of success was repeated when classifying the Haplogypsids Order at the two designated pedons, in addition to the complete match in the Haplocalcids classification across all five studied pedons. Thus, the overall classification accuracy was 100%.

Table (8) Confusion Matrix between Field Data and Program Outcomes at the Great group

Confusion matrix		Program					
		Torrifluvents	Aquisalids	Haplosalids	Haplogypsids	Haplocalcids	Total
Field Work	Torrifluvents	4					4
	Aquisalids		5				5
	Haplosalids			2			2
	Haplogypsids				2		2
	Haplocalcids					5	5
	Total	4	5	2	2	5	18

Subgroup:

At the Subgroup level, the results showed that the soils fell into 8 categories. The comparison results are included in Table (9), which represents the Confusion Matrix between the fieldwork classification (the baseline) and the program classification.

Regarding the classification of the Aquic Torrifluvents Subgroup, the program successfully classified 4 out of 4 pedons under this category. Statistical results indicated a 100% success rate for the program in classifying the Gypsic Aquisalids Subgroup, correctly classifying 2 out of 2 pedons. The program also correctly classified 3 out of 3 pedons that experts had classified as Typical Aquisalids. Similarly, the program successfully classified 2 out of 2 pedons for the Gypsic Haplosalids Subgroup.

The program also demonstrated accuracy in classifying soils for the Leptic Haplogypsids Subgroup, successfully classifying 1 out of 1 pedon. It also correctly classified 1 out of 1 pedon for the Typical Calcigypsids subgroup. It also successfully classified 3 out of 3 pedons within the Aquic Haplocalcids Subgroup and 2 out of 2 pedons within the Typic Haplocalcids Subgroup. Overall, the results indicate that the program correctly classified all 18 pedons, achieving an overall classification accuracy of approximately 100% at the Subgroup.

This 100% accuracy is primarily attributed to the fact that the classification and judgment were made by a single individual -the researcher. However, this percentage might change if the descriptor were different.

Table (9) Confusion matrix between field data and program results at the subgroup level

Confusion matrix		Program								
		Aquic Torrifluvents	Gypsic Aquisalids	Typic Aquisalids	Gypsic Haplosalids	Leptic Haplogypsids	Typic Calcigypsids	Aquic Haplocalcids	Typic Haplocalcids	Total
Field Work	Aquic Torrifluvents	4								4
	Gypsic Aquisalids		2							2
	Typic Aquisalids			3						3
	Gypsic Haplosalids				2					2

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	Leptic Haplogypsids					1				1
	Typic Calcigypsids						1			1
	Aquic Haplocalcids							3		3
	Typic Haplocalcids								2	2
	Total	4	2	3	2	1	1	3	2	18

CONCLUSIONS AND RECOMMENDATIONS:

1- The SmartSoil Classifier program demonstrated high efficiency in automating soil classification according to the Soil Taxonomy 1999 and keys to soil taxonomy 2022. It achieved very high accuracy at the higher (Order and Sub-order) classification levels, confirming the possibility of replacing a large portion of office work with a digital system.
2- The study showed that recalibrating the reference data and correcting human errors can theoretically raise the program's accuracy to 100% at most classification levels, thus enhancing its reliability as a scientific tool.
3- The results indicated that most discrepancies between the program and experts stemmed from errors in the reference data, not from flaws in the algorithm itself. This demonstrates the superiority of digital processing in adhering to classification rules.
4- The program successfully identified subtle characteristics, such as the presence of surface gypsum horizons (leptic) and the exclusion of unverified sodicity details often overlooked in traditional field characterization.
5- The selected soils under study fall within the Aridisols and Entisols orders and reflect an arid environment with a hyperthermic temperature regime. The study also revealed a predominance of recently formed or poorly developed soils.
6- The study highlighted the dominance of soil-forming processes such as salinization, gypsification, and calcification in the study areas, leading to the accumulation of salts, gypsum, and carbonates in the soil.
7- The absence of evidence of illuviation, such as clay skins, confirms the lack of argillic horizons and indicates that the variation in clay is due to sedimentation rather than pedogenic evolution, thus explaining the dominance of the A–C sequence.
8- The study showed that the variation in soil properties is strongly correlated with physiographic units (Basins, River levee, Depressions), which affects soil texture and salinity, as well as the distribution of carbonates and gypsum.
9- The study confirms that the best results are achieved by combining human experience with digital systems rather than relying on either alone.

RECOMMENDATIONS:

1- We recommend using the SmartSoil Classifier software in soil survey projects and agricultural and research institutions to reduce time and cost and increase the accuracy of soil classification.
2- It is essential to establish an accurate digital database of soils in Iraq to serve as input for smart software and a reference for updating maps in agricultural projects prepared by official state institutions.
3- Improving the quality of field data is crucial, as the accuracy of the software depends on the quality of input. Therefore, we recommend training surveyors and standardizing morphological description methods to reduce discrepancies among experts.
4- Integrating advanced artificial intelligence technologies by developing the software in the future using deep learning, remote sensing, and geographic information systems to enhance spatial prediction efficiency.
5- Developing the software to include soil classes other than Aridisols and Entisols found in Iraqi soils in particular and globally in general, and applying it in different environments both inside and outside Iraq.

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