SMALL-AREA POPULATION FORECASTING OF SHRINKING CITIES IN SOUTH KOREA: USING SHAP(SHAPLEY ADDITIVE EXPLANATIONS) MACHINE LEARNING (1127)

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Abstract. The purpose of this study is to identify the utility of machine learning model in projecting the population of small areas. This study was conducted between 2020 and 2040 in the local districts of Korea and compared the research results of cohort-component model and machine learning model. As a result of projecting population through the cohort-component method and machine learning, it was identified that the accuracy of the machine learning model was much higher. The cohort-component model is expected to have a high forecasting error because it only explains population change by three component: birth, death, and migration, and it is confirmed that it is almost unpredictable, especially when there are frequent population changes due to new development. On the other hand, the machine learning model reflects various variables such as socioeconomic factors in the population projecting model, which greatly reduces the prediction error. The machine learning model projected that the population would be evenly distributed across the country, especially on the central part of Busan Metropolitan City, while the cohort-component model projected that the population would be concentrated in some areas such as Gijang-gun and Gangseo-gu. The SHAP value interpreted as the machine learning model relying most heavily on the pre-population and fertile women variables to project population.

Keywords: Small-area Population Projection, Cohort-Component Method, Machine Learning, SHAP.

1. Introduction

Population data is the basis of urban planning and various policy data and is an essential leading indicator. This is because changes in the population structure not only affect all areas such as housing, economy, welfare, and environment, but also determine the size of urban planning facilities and service supply standards based on predicted population data. In other words, population is the most basic data for estimating demand in all areas encompassing cities. Therefore, inaccurate population prediction causes idle capital or congestion costs, causing social inefficiency and degrading the quality of the entire city. This means that a professional understanding of the population structure and size is required for sustainable national land construction, and accurate population estimation should be in the first stage when establishing a basic urban plan.

In the era of population decline, questions about the rationality of future population estimates have led to the need for population prediction at a more detailed unit independent of administrative district boundaries. In fact, a lot of research and policies related to population estimation in small regions have recently been discussed domestically and internationally, and research methods that can increase the accuracy of population prediction in small regions are also being devised. (Wilson, 2015; Inoue, 2017). Statistical techniques used in the existing population estimation process only predict population change trends based on past populations, and there is a limit to setting factors that affect population size and fluctuations. Therefore, the socioeconomic characteristics or regional specificity of the region cannot be considered. Population estimation in small areas should be carried out based on scientific evidence based on big data, away from traditional statistical techniques, as it must ensure the accuracy of high-resolution data.

In this context, the grid-based future population prediction model using artificial intelligence techniques can not only diagnose detailed and specific national land phenomena but also reflect nonlinear relationships between factors that affect population fluctuations. Therefore, the purpose of this study is as follows. This study aims to predict the future population distribution of 500m grid units in Busan, Korea from 2020 to 2040 by applying cohort factor method and machine learning algorithms, which are commonly used population estimation techniques, and to develop a more appropriate future population prediction model for small areas. Accordingly, interpretable machine learning was applied to understand the linear or nonlinear relationship between factors affecting the future population.

The study is conducted in the following order. Section 2 examines research trends related to population estimation and interpretable machine learning in small areas. Section 3 explains the research model and data set in this study based on the theoretical background identified in Section 2. Section 4 presents the research results, and Section 5 presents the conclusions of the study and future research directions.

2. Theoretical background

2.1. Population Projection and Forecasting Error

Demographic discussions regarding future population prospects generally use the terms 'projection' and 'forecasting', but technically the two concepts are different. Projection is a conditional statement of future population based on assumptions related to population fluctuation factors, while forecasting(prediction) is defined as a statement about estimating the most likely future realization value based on scientific knowledge (Smith, Tayman, & Swanson, 2001, p.3). In terms of the projection and forecasting concept, forecasting always corresponds to projection, but the inverse is not established (Wilson & Rees, 2005). In reality, population prediction is named population projection, which seems to be due to the inevitable error in predicting the future population. This mix of terms between demographers and population data users rather indicates that population projection is necessary due to the uncertainty of these data (Shaw, 2007). Alternatively, the degree of error and uncertainty of the predicted result value should be clearly presented.

The reasons for using the concept of estimation in existing population estimation studies are as follows. First, the process of predicting the future population is meaningful just by looking at the figures under certain conditions if the presented assumption is logical and there is no error in the formula process, regardless of future feasibility. Second, given that perfect prediction is impossible, it is more productive to discuss how to reduce uncertainties arising from the process of population forecasting rather than distinguishing the definition of estimation and prediction. In addition, population estimation work does not allow a wide margin of error or mechanically repeat simple conditions and assumptions, but rather involves deriving the most accurate values with some future feasibility in mind.

This study was used in accordance with the methodology using both concepts of estimation and prediction. The cohort-component method, which is a methodology that only estimates the prospective population in the future by considering only three factors that affect the structure of population fluctuation, is named population projection. On the other hand, in the case of machine learning techniques that predict values close to actual values by reflecting more realistic and diverse variables based on big data and high-end computers, population forecasting was mentioned.

Forecast Error(FE), an indicator of the accuracy of population estimation results, is defined as the difference between the population forecast value and the actual population value at the time of the estimated target year. This means the absolute value of the error, and in reality, the percentage error (PE) is used more than the absolute value of the error. Marking the error as a percentage is useful when you want to compare the result values relatively.

In some cases, there are multiple predictions for a point in time and for a particular year. This includes cases where future population estimates for various regions are conducted at the same time or where several predictions exist in a specific time series section. In this case, it is useful to present the average value of errors such as ME (Mean Error) and MAE (Mean Absolute Error). ME may not be able to present an accurate error due to offsetting of positive and negative values in the calculation process, while MAE means the average absolute value of errors, so cumulative error calculation is possible. However, ME and MAE are also easier to interpret and more applicable when marking their values as percentages. However, high inaccuracy can be derived due to the influence of extreme values or offset of errors, respectively, MPE (Mean Percentage Error), a percentage substitution value of ME, and MAPE (Mean Absolute Percentage Error), a percentage substitution value of MAE.

Accordingly, the difference between the predicted value and the actual value is squared and presented as MSE (Mean Squared Error), and if the error is squared, the effect of the extreme can be excessively reflected, so RMSE (Root Mean Squared Error), the square root of MSE, is also used. A schematic representation of the type of prediction error that measures the accuracy of population estimation is as follows.

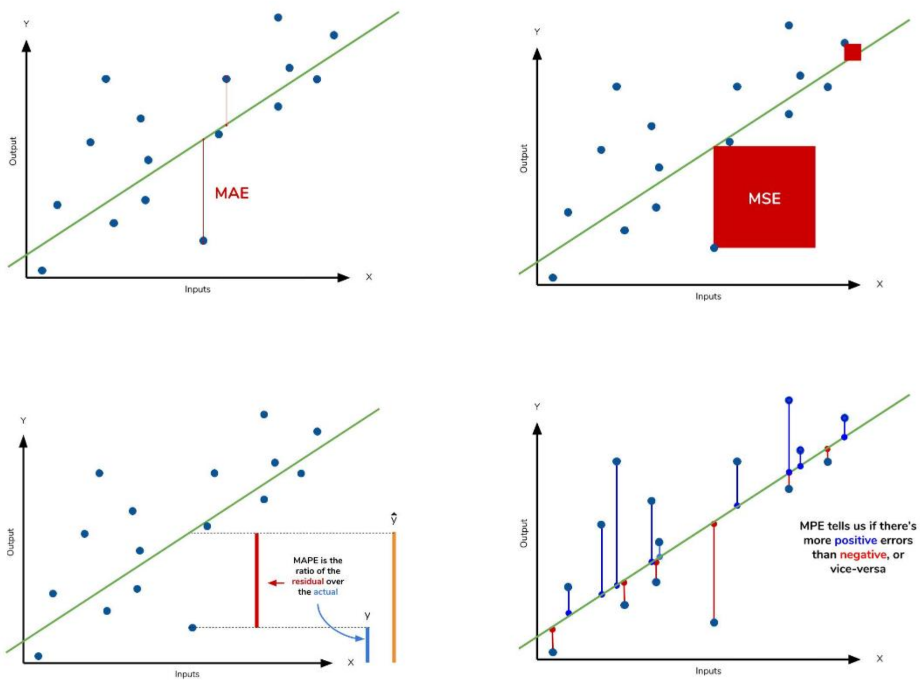

Figure 1. Accuracy of Population Projection

2.3. Small-Area Population Projection

One of the main trends in demographics is the demand for population estimation in small areas (Cai, 2007). Estimating the population of small areas is useful in that governments and companies can present more accurate investments when investing in new infrastructure or providing local services, or point to specific areas where services should be provided intensively. However, despite the usefulness and necessity of small-area population estimation research due to inversely proportional prediction accuracy and rapidly changing demographic environment as spatial resolution is increased, related studies are still insufficient. (Wilson et al., 2023). The reasons for the difficulty in estimating the population of small areas and slow interdisciplinary development are largely as follows. First, most population prediction models, such as the cohort factor method, have been developed to address population structures within the macrogeographic range. When applying this prediction model to small areas, it is difficult to guarantee the reliability of the research results due to the lack of spatial resolution. Next, in the case of small areas, non-personal factors such as social environment context and land use that traditional population prediction models do not consider play a greater role as variables. Therefore, the second reason can also be seen as emphasizing that there is a limit to applying the traditional population prediction model to small areas (Chi et al., 2011). In recent years, the field of population estimation in these small areas has been increasing its potential due to the development of the big data field and the development of new technologies that exceed human capabilities.

Although there is no universal definition of small areas in the demographic field, small areas are generally considered the most detailed spatial unit among the regional classifications for which data can be obtained (Smith and Morison, 2005). Examples of representative small areas in previous studies include Statistical Area Level 2 in Australia, sensor tracks in the United States, Ward and census areas in the United Kingdom, and most of the populations in those areas are less than 20,000 (Wilson, 2015). Most of the studies related to small areas in Korea have been conducted at the city, county, and district levels, and these studies are focusing on the process of increasing the accuracy of population prediction due to population movement. However, as the demand for population prediction for more detailed areas increases, the unit of small areas is gradually narrowing to a narrower range such as eup, myeon, dong, aggregate, and grid. In recent years, research on how to predict grid-level population has been conducted at home and abroad, and accordingly, public and private sectors such as the National Geographic Information Service and mobile carriers are producing grid-level statistical data to support the research fiel.

Various methodologies are used to increase the accuracy of prediction in small-area population estimation studies. The methodologies used in related previous studies are largely classified into basic models, cohort factor methods, spatial statistical models, scenario-based models, and artificial intelligence techniques. The basic model is again divided into trend extrapolation and ratio, and these models require minimal data and have the advantage of simplifying the calculation process, but as the prediction period increases and the region decreases, the prediction error increases and changes in the population structure cannot be explained. The cohort factor method is the most commonly used population estimation methodology, and is a method of estimating future populations by creating a population balance equation for the three factors of population change: birth, death, and movement. In the case of the cohort factor method, in the past, it simply remained in the accounting method considering the number of births, deaths, and transfers and transfers in the base population, but recently, it has been advanced by applying probability and regression mo. The Kocht factor method is a population forecast method that is widely used in recognition of its reliability by capturing population change patterns well, but it still has limitations to apply to small regional units. This is because it is difficult to calculate the factors of population change considered by the cohort factor method at a microscopic level. The spatial statistical model and spatio-temporal regression model have the advantage of reflecting the interrelationship between adjacent spaces overlooked by existing demographic methodologies, but prior studies show that the prediction error is not significantly reduced compared to simple regression. (Chi·Voss, 2011). Unlike the aforementioned methodologies, it is a technique that simulates future changes or predicts future populations based on theoretical backgrounds and socioeconomic and physical environmental contexts related to population change. It can be seen that scenarios are mainly organized according to land use and future development plans and urban basic plans announced by each local government, and future populations are estimated for each scenario. (Triantakonstantis·Mountrakis, 2012; Ford et al., 2019; Chen et al., 2020). This scenario-based future population estimation method has the advantage of reducing errors in predictions by reflecting land use plans and various urban population variables, but like existing demographic models such as the cohort factor method, there are limitations in the stage of building small-area data. In addition, demographic factors and natural population growth factors are relatively neglected in the population outlook and are not accepted by demographers.

Artificial intelligence techniques, a methodology used in this study, began to be applied to the population estimation system three to four years ago, and most of the population estimation studies using machine learning techniques compare whether the population prediction performance of machine learning models is significant compared to existing population estimation techniques. (Riman et al., 2019; Grosman, 2022·Tilson). Riiman et al. (2019) compared the results of the ANN (aromatic neural network) long-short term memory (LSTM) for the county area of Alabama and the results of the cohort factor method. The study presented two types of models in which data from all counties were learned in batches and models learned separately for each county. The most predictive case was when the ANN LSTM model was learned for each county, and the MAPE of this model was 5%, proving its usefulness as a population estimation model. Chen et al.

(2020) predicted the population distribution every five years from 2015 to 2050 using four artificial intelligence algorithms: XGBoost, Random forest, Neural network, and Support vector regression. This study attempted to derive realistic results by reflecting spatial variables related to population distribution such as land use and distance to urban centers in future population estimation. Grossman et al. (2022) tried to confirm the usefulness of the ensemble technique of machine learning, a technique that combines several models when predicting population. Accordingly, six models were applied: CSP (constant share of population), MEX (modified expansion model), VSG (variable share of growth model), LIN/EXP (linear/exponential), THETA, and LGBM (light gradient boosting model), and the subject of the study is SA and New Zealand. There are two methods of merging models: to derive the average value of the total model result value or to derive the average value excluding the maximum and minimum values of each model. Studies have shown that including the LGBM model improves the accuracy of the population prediction model, which has been confirmed that machine learning algorithms contribute to the reliability of population prediction in small areas. In addition, studies using LSTM algorithms that enable time-series population change trend learning or machine learning techniques, a technique for estimating future populations through past data learning related to population change, are emerging. (Weber, 2020; Grossman, Wilson, Temple, 2022).

Accordingly, it can be seen that artificial intelligence techniques such as machine learning have been applied to the field of population estimation in small areas since the past three to four years. (Riman et al., 2019; Grossman et al., 2022, Grossman·Wilson·Temple, 2022). Most of the studies that conducted population estimation in small areas using machine learning techniques aim to compare machine learning techniques with other future population estimation methods to determine whether the population outlook in small areas is significant.

3. Data and Methods

3.1. Data and Variables

This study takes Busan Metropolitan City, Korea as the spatial scope of the study. Busan Metropolitan City is seen as a representative shrinking city in Korea due to the outflow of population to the metropolitan area and the serious low birth rate. As a characteristic, the population continues to decline, aging, and the number of aging infrastructure such as abandoned houses continues to increase. The purpose of this study was to supplement the existing population estimation process when the population distribution is expected to be local due to local extinction.

The spatial scope of this study is the 500m*500m grid unit in Busan, Korea. Grid unit data were constructed using grid unit population indicators and other variables provided by the National Geographic Information Service. Grid unit data provided by the National Geographic Information Service are provided for 100m, 250m, 500m, and 1km, and this study used 500m grid unit indicators. The urban planning implication of the 500m grid space unit in Korea is neighborhood housing. Although it does not legally and institutionally present a clear radius and area for neighborhood housing, according to Perry, who proposed the concept of neighborhood housing, the radius is about 500m grid units. Neighborhood districts are defined as the size of children's safe commuting to school as a unit of planning, or the range of average attachment to the community of residents.

The time range of the study is from 2020 to 2040. This requires the basic urban and county plans to be established based on 20 years from the base point, and the census is a part of Korea's urban planning basis, which is established every five years. In addition, before conducting population estimation using each methodology, the study predicted the population in 2020 using data from 2000 to 2020, and calculated the error compared to the actual population in 2020. This error is the percentage difference from the estimated 2020 population compared to the actual 2020 population.

3.2. Method

3.2.1. Cohort-Component Method

In estimating the future population, this study applied two population estimation methods: cohort factor method and machine learning. The cohort factor method is a method of calculating population values for each cohort by largely classifying population changes into birth, death, and population movement. In the cohort factor method, a cohort refers to a population group whose birth time matches in n-year-olds, and mainly uses a 5-year-old interval. Therefore, the cohort factor method is summarized in the following equation as follows. The cohort factor method is applied as a universal national future population estimation method because it is easy to understand demographic changes and apply them to policies (Smith et al., 2013).

(Equation 1) $P_t = P_{t-1} + B_{(t-1,t)} - D_{(t-1,t)} + M_{(t-1,t)}$

(P_t : population at time t, $P_{(t-1,t)}$: population at time t-1, $B_{(t-1,t)}$: birth population, $D_{(t-1,t)}$: dead population, $M_{(t-1,t)}$: net moving population)

3.2.2. Machine Learning

The study applied machine learning techniques as the second model of population estimation. Machine learning can be said to be a process in which humans do not build logic directly, but enter learning methods first and create logic on their own. Algorithms are created in the process of creating logic so that machines can make decisions, and many of the machine learning algorithms in the past were impossible to implement due to lack of computational power. However, in modern times, complex operations have become possible due to the development of hardware performance, and a number of algorithms have been developed that can process vast amounts of data at high speed. The machine learning algorithm used in this study is XGBoost (Extreme Gradient Boosting).

XGBoost is one of the boosting algorithms, a way to provide stronger classification performance by stacking several weak classifiers (tree models) (Chen and Guestrin, 2016). The boosting algorithm is an algorithm that performs classification by a single tree and then weights misclassified cases to correct classifiers and improve performance.

3.2.3. XAI: Explainable Artificial Intelligence

Machine learning or deep learning models that have recently been used in many fields show high performance and low error rates through complex structures that existing statistical techniques cannot implement, but there is a limitation in that it is difficult to explain the process of deriving results due to the complex structures. However, only when the result value of the model can be understood and interpreted can the model be trusted and the basis for the result can be presented (Lundberg and Lee, 2017). XAI is a technique introduced to compensate for these problems of machine learning and deep learning, and XAI is a technique that adds the possibility of explanation so that the artificial intelligence model can know on what basis the decision was made until a specific conclusion was made. XAI is also called interpretable artificial intelligence or transparent artificial intelligence, and decision tree visualization, feature importance, and partial dependency plot (PDP) have previously been used as XAI methods, but LIME (Local Interpretable Model) and SHAP techniques have recently been introduced.

In other words, XAI is a technology that decomposes the black box tendency of the machine learning model to a level that humans can understand. In the end, the possibility of understanding artificial intelligence refers to the process of changing the basis of decisions made by machine learning so that humans can understand. Feature Importance, one of the basic techniques of XAI, measures which features contributed the most to the model's decision-making process. If the feature importance has a negative value, the feature cannot always be said to be helpful in decision-making, but it is possible to determine which data the model handles with weight while measuring the feature importance.

Another method for interpreting machine learning used in this study is SHAP (Shapley Additive exPlanations). SHAP is an XAI that uses Shapley Value and independence between features as key ideas. The Shapley value numerically expresses how much each variable contributed to generating overall performance. According to the Shapley value, the contribution of each variable can be expressed as the degree of change in overall performance when the contribution of the variable is excluded. This logic is based on game theory, and the degree to which the i-person contributes to the overall performance when many play the game is based on the total contribution minus the sum of the contributions excluded by the i-th person.

Unlike the existing regression analysis, it can be applied even when independent variables predicting dependent variables are dependent on each other, and it is advantageous in that it can provide the basis for the influence of individual independent variables and the influence of individual independent variables.

4. Findings

4.1. Cohort-Component Method

Before applying each methodology to immediately proceed with population estimation, the reliability of this methodology was determined by comparing the consensus between the estimated population value and the actual population value for 2020 using the cohort factor method. Table 1 shows the results of population estimation using the cohort factor method from 2000 to 2020. Except for Gangseo-gu and Gijang-gun, which are currently most likely to be developed in Busan, the error between the estimated population and the actual population is 23% on average. In addition, if the cohort factor method was applied, it was predicted that the population of Busan would increase by 560,000 from the actual population value.

Most of the errors in the cohort factor method were derived from the process of estimating population movement and the process of estimating the age population in their 20s and 40s. Both processes are regions with large time-series variations and large population fluctuations for the estimation period and forecast period. This indicates that the cohort factor method has a limit to predicting the rate of population change due to social and economic factors, simply considering the increase or decrease in population, fertility rate, and survival rate at the previous time.

Table 1. Cohort-Component Method Analysis Error

Area		Sex	Projected Population in 2020	Actual Population in 2020	Error(%)
Busan		Male	1,317,651	1,638,751	19.59
		Female	1,472,815	1,710,265	13.88
Municipality	Junggu	Male	14,039	20,416	31.24
		Female	16,039	21,019	23.69
	Seogu	Male	34,940	51,127	31.66
		Female	38,883	54,172	28.22
	Donggu	Male	17,726	42,453	58.25
		Female	20,478	44,791	54.28
	Yeongdogu	Male	37,734	56,613	33.35
		Female	45,004	56,610	20.50
	Jingu	Male	141,579	168,641	16.05
		Female	165,111	182,762	9.66
	Dongnaegu	Male	70,711	127,743	44.65
		Female	83,048	135,600	38.76
	Namgu	Male	130,011	131,683	1.27
		Female	143,259	137,426	4.24
	Bukgu	Male	195,608	138,110	41.63
		Female	208,643	142,066	46.86
	Haeundaegu	Male	165,812	187,806	11.71
		Female	189,946	201,729	5.84
	Sahagu	Male	135,163	155,310	12.97
		Female	148,028	156,746	5.56
	Geumjeonggu	Male	74,961	115,296	34.98
		Female	85,107	121,919	30.19
	Gangseogu	Male	8,728	72,093	87.89
		Female	10,043	64,639	84.46
	Yeonjegu	Male	84,903	98,184	13.53
		Female	93,996	106,760	11.96
	Sooyeonggu	Male	68,568	80,698	15.03
		Female	80,313	90,760	11.51
	Sasanggu	Male	95,824	108,759	11.89
		Female	103,264	107,589	4.02
	Gijanggun	Male	41,344	83,787	50.66
		Female	41,654	85,677	51.38

Next, population estimation was conducted using the cohort-component model for 2020-2040 in consideration of an average error of 23%. Table 2 shows the results of each city, county, and district of Busan Metropolitan City that conducted population estimation. As shown in the results of the 2020 population estimate, a rapid decrease in population was expected in all regions except Gangseo-gu and Gijang-gun. Comparing the estimated population in 2035 with the population in 2040, it can be confirmed that the population of Busan Metropolitan City will continue to decrease, especially Yeongdo-gu, Sasang-gu, Jung-gu, Seo-gu, and Busanjin-gu. In addition, as a result of calculating the PC (Percent Change) value that can confirm the increase or decrease in the population in the estimated year compared to the base year, it can be seen that the total estimated population in Busan will decrease by 26.7% on average compared to 2020.

4.2. Machine Learning

Like the cohort factor method, the error and reliability of this methodology were first determined after comparing the actual 2020 population value with the estimated value for 2015-2020. Table 3 shows the results of estimating the population of Busan using the machine learning algorithm. Unlike the cohort factor method, which derived an average error of 23%, it can be confirmed that the error range plunges to the 3% range when population estimation is performed using machine learning. When applying the cohort factor method, it was confirmed that machine learning techniques could be applied to Gangseo-gu and Gijang-gun, which had the largest error range, to derive high accuracy results when estimating the population. In addition, as a result of deriving the RMSE value, an indicator of the accuracy of the XGBoost model used in this study, it was found to be 48.27.

As a result of estimating and summing the population of each small area in Busan using the XGoost algorithm, the total population of Busan in 2040 is expected to decrease by 1.75% compared to 2020. As a result of the machine learning analysis, the top five regions that are expected to show the most rapid population change compared to 2020 were Yeongdo-gu, Geumjeong-gu, Jung-gu, Dong-gu, and Seo-gu, and all 15 cities and counties in Busan except Haeundae-gu and Gangseo-gu.

The results of estimating the population of Busan Metropolitan City by applying the XGBoost technique among the cohort factor method and machine learning algorithm are as follows. Machine learning analysis techniques derived relatively much higher accuracy in estimating the population of small areas in Busan, Korea, and both methodologies estimated that the population of Yeongdo-gu, Jung-gu, and Seo-gu would decline the most. Both methodologies estimated that the population of Busan would continue to decrease, and as a result of identifying the population by age through the cohort factor method, the decrease in the population of Busan can be interpreted as the share of the continuously decreasing young population.

It can be seen that the cohort factor method, which does not reflect various factors in the population estimation process and uses only birth, death, and migrant population as variables, produces almost inaccurate results for Gangseo-gu and Gijang-gun areas where population inflows are expected to occur most actively. On the other hand, the machine learning technique can reflect a combination of various variables that may affect changes in the population structure, resulting in a lower error, indicating that it is highly applicable to estimating areas with large population changes.

The results of estimating the population for a 500-meter grid in Busan are shown in Figure 2 and Figure 3. Intuitively, we can see that the cohort factor method predicts a sharp decline in population compared to the machine learning method. In addition, the cohort factor method predicts that the population of Gijang-gun and Gangseo-gu will be relatively high for each municipal district in Busan in 2040, while the machine learning method predicts that the municipal districts of Busan will have a global population distribution except for Sahagu, Yeongdo-gu, and Jung-gu.

Table 2. Cohort-Component Method Analysis Result

Area		Sex	Projected Population in 2035	Projected Population in 2040	2035 Percent Change (%)	2040 Percent Change (%)
Busan		Male	1,284,881	1,139,738	-21.6%	-30.5%
		Female	1,442,910	1,321,865	-15.6%	-22.7%
Municipality	Junggu	Male	12,330	9,450	-39.6%	-53.7%
		Female	13,747	11,035	-34.6%	-47.5%
	Seogu	Male	33,415	26,873	-34.6%	-47.4%
		Female	38,202	31,924	-29.5%	-41.1%
	Donggu	Male	33,239	29,125	-21.7%	-31.4%
		Female	37,098	33,379	-17.2%	-25.5%
	Yeongdogu	Male	25,715	16,371	-54.6%	-71.1%
		Female	27,516	17,794	-51.4%	-68.6%
	Jingu	Male	108,132	86,217	-35.9%	-48.9%
		Female	130,647	110,587	-28.5%	-39.5%
	Dongnaegu	Male	110,834	102,321	-13.2%	-19.9%
		Female	127,878	121,927	-5.7%	-10.1%
	Namgu	Male	91,174	76,253	-30.8%	-42.1%
		Female	101,864	87,657	-25.9%	-36.2%
	Bukgu	Male	97,200	81,182	-29.6%	-41.2%
		Female	108,471	95,044	-23.6%	-33.1%
	Haeundaegu	Male	140,309	121,735	-25.3%	-35.2%
		Female	162,733	146,425	-19.3%	-27.4%
	Sahagu	Male	108,474	90,369	-30.2%	-41.8%
		Female	118,047	102,698	-24.7%	-34.5%
	Geumjeonggu	Male	83,041	70,516	-28.0%	-38.8%
		Female	96,528	85,846	-20.8%	-29.6%
	Gangseogu	Male	123,466	136,528	71.3%	89.4%
		Female	114,165	127,502	76.6%	97.3%
	Yeonjegu	Male	84,606	77,879	-13.8%	-20.7%
		Female	104,846	101,301	-1.8%	-5.1%
	Sooyeonggu	Male	66,141	59,666	-18.0%	-26.1%
		Female	84,387	79,883	-7.0%	-12.0%
	Sasanggu	Male	61,023	45,135	-43.9%	-58.5%

Area		Sex	Projected Population in 2035	Projected Population in 2040	2035 Percent Change (%)	2040 Percent Change (%)
		Female	67,095	53,736	-37.6%	-50.1%
	Gijanggun	Male	105,781	110,116	26.2%	31.4%
		Female	109,689	115,125	28.0%	34.4%

Area		Projected Population in 2020	Actual Population in 2020	Error(%)
Busan		3,428,035	3,349,016	2.36%
Municipality	Junggu	41,941	41,439	1.21%
	Seogu	108,214	105,303	2.76%
	Donggu	87,733	87,246	0.56%
	Yeongdogu	117,224	113,224	3.53%
	Jingu	358,557	351,403	2.04%
	Dongnaegu	260,425	263,345	1.11%
	Namgu	282,192	269,111	4.86%
	Bukgu	309,385	280,177	10.42%
	Haeundaegu	400,241	389,535	2.75%
	Sahagu	316,903	312,057	1.55%
	Geumjeonggu	236,116	237,219	0.46%
	Gangseogu	131,037	136,734	4.17%
	Yeonjegu	213,129	204,947	3.99%
	Sooyeonggu	176,373	171,461	2.86%
	Sasanggu	221,165	216,350	2.23%
	Gijanggun	167,400	169,465	1.22%

Table 3. Machine Learning Analysis Error

Area		Actual Population in 2020	Projected Population in 2040	Percent Change(%)
Busan		3,349,016	3,290,566	-1.75%
Municipality	Junggu	41,439	38,977	-5.94%
	Seogu	105,303	101,423	-3.68%
	Donggu	87,246	83,249	-4.58%
	Yeongdogu	113,224	103,888	-8.25%
	Jingu	351,403	346,271	-1.46%
	Dongnaegu	263,345	260,335	-1.14%
	Namgu	269,111	263,791	-1.98%
	Bukgu	280,177	277,818	-0.84%
	Haeundaegu	389,535	398,235	2.23%
	Sahagu	312,057	305,201	-2.20%
	Geumjeonggu	237,219	218,156	-8.04%
	Gangseogu	136,734	143,420	4.89%
	Yeonjegu	204,947	202,069	-1.40%
	Sooyeonggu	171,461	170,791	-0.39%
	Sasanggu	216,350	208,427	-3.66%
	Gijanggun	169,465	168,515	-0.56%

Table 4. Machine Learning Analysis Results

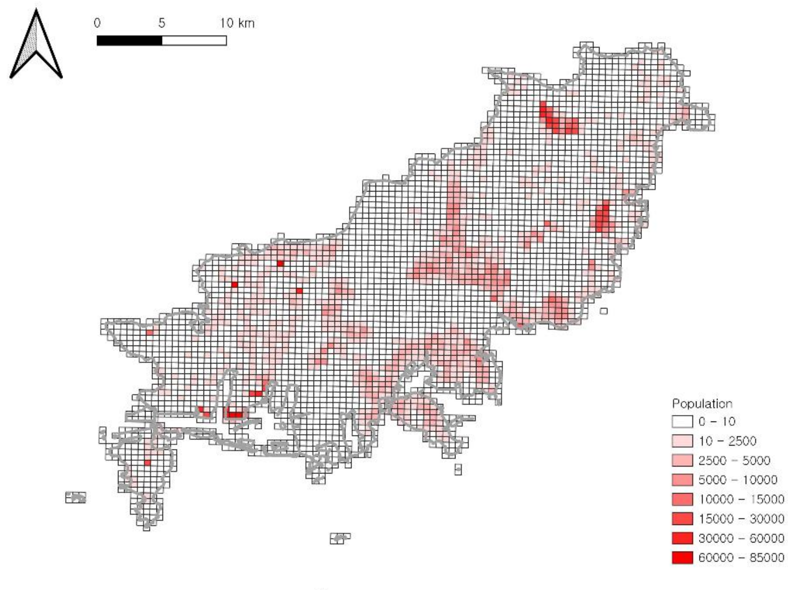

Figure 2. Results of 2040 Population Estimated by Cohort-Component Method

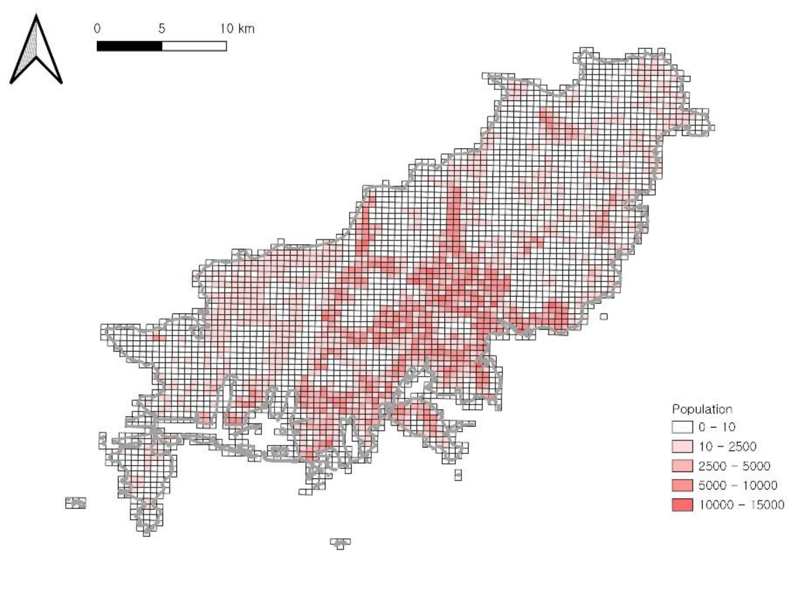

Figure 3. Results of 2040 Population Estimated by Machine Learning

4.3. XAI(Explainable Artificial Intelligence)

Figure 3 shows the results of interpreting the XGBoost algorithm by visualizing the importance of the peer among the XAI techniques. According to the feature importance graph, it can be seen that the XGBoost algorithm affects the population estimation of Busan in the order of productive female population, former population, number of houses, elderly population, and old housing ratio.

As a result of analyzing the Shapley value, it can be seen that this model is interpreted similarly to the result of the feature importance technique. The red dot in Figure 4 means that the variable had a great influence on the population estimate, while the blue dot can be interpreted as having a small effect on the determination of the population estimate. The Shapley value is interpreted to affect population estimation in the order of pre-population, productive female population, elderly population, individual housing, and old housing ratio, and in particular, pre-population variables and productive female population variables play a large role. The variance of the two variables is also large. According to Figure 4, it can be seen that the accuracy and judgment of population estimation depend greatly on the number of population at the time and the number of productive women, and other variables do not have a great responsibility for population estimation.

The difference between the feature importance and the Shapley value is the assumption of the independence of the variable. Feature importance does not assume the independence of variables, so if the dependence between variables is large, the results are likely to be distorted, and feature importance does not calculate negative influences (factors that affect population decline). This is because the feature importance technique does not intentionally learn the negative (-) variable to lower the calculation error. Thus, feature importance techniques can over-measure the value of a particular variable than the actual value.

On the contrary, the Shapley value can consider the dependence between each variable assuming the independence of the variables, and can also consider the negative (-) influence. That is, the Shapley value may interpret the machine learning model by reflecting the influence of variables on a wide range that the feature importance does not consider.

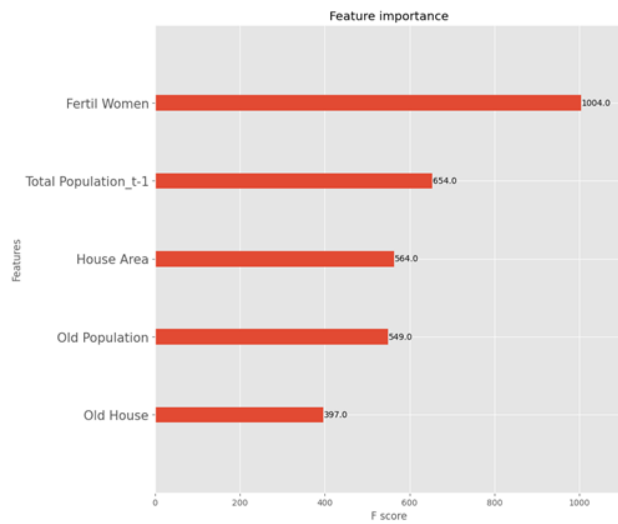

Figure 4. Feature Importance Analysis Results

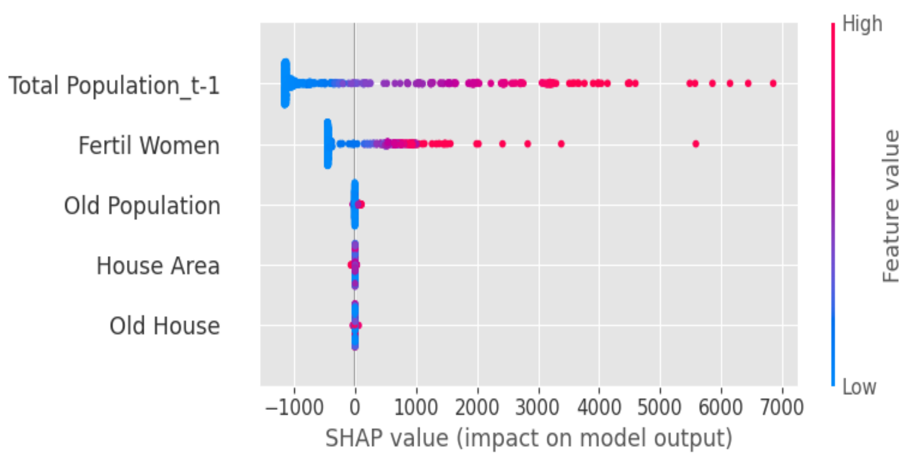

Figure 5. Shapley Value Results

5. Conclusion

The demographic structure and change of a country and region are not only affected by changes in the region, but also changes in the demographic structure itself act as a key factor in the change of the region. Therefore, it is necessary to predict and prepare for the exact cause of population structure and change and the possibility of future changes in advance, and the future population results estimated in this way function as major policy data in the region. However, despite the need to estimate the population from a more microscopic perspective due to the recent local extinction, low birth rate, and aging, it is time to consider the new population estimation method and the applicability of the methodology.

The purpose of this study is to identify the applicability of grid-level data and machine learning techniques in estimating the population of small areas, which are recently attracting attention, and to confirm the usefulness of interpreting machine learning models using SHAP values. By comparing the results of machine learning techniques with cohort factor methods used by the Korea National Statistical Office for future population estimation and traditional population estimation methods, this study proved that it is much more useful to apply machine learning techniques to population estimation in small regions. Furthermore, not only the machine learning result value was presented, but also the SHAP value was applied to the machine learning model used in this study to explain why the machine learning model derived the corresponding result value.

As a result of the analysis, it was confirmed that the application of machine learning techniques in estimating the population of small areas in Korea's grid unit showed a much improved value in terms of estimation accuracy, which can be said to be due to the nature of machine learning techniques that can take into account social and economic contexts and other environmental characteristics that statistical methodologies are difficult to predict. The population of Busan Metropolitan City, South Korea, estimated through machine learning techniques in 2040 was 3,290,566, a 1.75% decrease from the population in 2020. As a result of analyzing the machine learning model using SHAP values, it was found that when estimating the population of small areas using the XGBoost algorithm, the variables that most positively (+) affect the result value were the population at the previous time and the productive female population. It was confirmed that other variables included in this model did not have a negative (-) influence compared to the previous population and the productive female population variables, indicating that the future estimated population results greatly depend on the past population values.

The result of the 2040 future population estimate published by the Korea National Statistical Office is 2,826,940. In this study, the population of Busan Metropolitan City in 2040 estimated using the XGBoost algorithm was 3,290,566, which is 463,626 more than the official results of the National Statistical Office. This can be interpreted as an underestimation of the population of Busan Metropolitan City in 2040 by Statistics Korea. This population underestimation and estimation error can be attributed to migration, births, deaths, and other unpredictable factors that can affect population change.

This study differs from other studies in that it was intended to present higher-level results using 500m grid data and to provide accurate population estimation results and explanatory power through machine learning techniques, unlike Korean research trends that have conducted up to 1,000m grid units. In addition, it has academic significance in that it uses XGBoost models with high predictive performance while providing an explanation of machine learning black boxes using XAI techniques such as feature importance and SHAP. Although a highly predictive model was implemented, there was no way to interpret the model, so there was a limit to the reliability and explanatory power of the research results. This study provided a great academic contribution as it could interpret the improved research results and the inside of the improved model.

However, if various small-area population estimation methodologies are presented through the application of more algorithms with high predictive performance other than the XGBoost algorithm, it will be helpful for future small-area population estimation studies. In addition, it is expected that the error of the machine learning model will be greatly reduced by adding variables that can deal with geological characteristics such as elevation and slope and broader socio-economic contexts as variables that can affect future populations.

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